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How Well Does Consumer-Based Brand Equity Align with Sales-Based Brand Equity and Marketing Mix Response?

Abstract

Brand equity is the differential preference and response to marketing effort that a product obtains because of its brand identification. Brand equity can be measured using either consumer perceptions or sales. Consumer-based brand equity (CBBE) measures what consumers think and feel about the brand, whereas sales-based brand equity (SBBE) is the brand intercept in a choice or market share model. This article studies the extent to which CBBE manifests itself in SBBE and marketing-mix response using ten years of IRI scanner and Brand Asset Valuator data for 290 brands spanning 25 packaged good categories. The authors uncover a fairly strong positive association of SBBE with three dimensions of CBBE—relevance, esteem, and knowledge—but a slight negative correspondence with the fourth dimension, energized differentiation. They also reveal new insights on the category characteristics that moderate the CBBE–SBBE relationship and document a more nuanced association of the CBBE dimensions with response to the major marketing-mix variables than heretofore assumed. The authors discuss implications for academic researchers who predict and test the impact of brand equity, for market researchers who measure it, and for marketers who want to translate their brand equity into marketplace success.

Key words: brand equity, consumer-based brand equity, marketing metrics, market share models, marketing mix elasticities.

Brand equity is a central construct in marketing theory and practice. Firms invest considerable effort over many years to build the equity of their brands. They reap the benefits of that investment in product market and financial market outcomes and leverage their brand equity to introduce brand extensions. The academic literature has studied each of these phenomena: building brands and their equity (Keller 1993); the association of marketing spending with brand equity (Sriram, Balanchander, and Kalwani 2007; Stahl, Heitmann, Lehmann, and Neslin 2012); the product market outcomes of brand equity such as market share, price premium, revenue premium, and profit premium (Ailawadi, Lehmann, and Neslin 2003; Goldfarb, Lu, and Moorthy 2009; Srinivasan, Park, and Chang 2005); the financial market outcomes of brand equity such as stock market returns, risk, and market value (Aaker and Jacobson 1994; Mizik and Jacobson 2008; Rego, Billett, and Morgan 2009); and the factors that enhance or limit a brand's ability to leverage its equity into brand extensions (Aaker and Keller 1990; Batra, Lehmann, and Singh 1993; Bottomley and Holden 2001). Hence there is a rich literature on the antecedents and consequences of brand equity.

However, what is brand equity and how is it measured? Perhaps the most widely accepted definition of brand equity is Keller's (1998) conceptualization: the different preference and response to marketing effort that a product obtains because of its brand identification as compared to the preference and response if that same product did not have the brand identification. Although there are almost as many measures of brand equity as researchers and consultants working in this area, there are two broad measurement approaches: based on what consumers think and feel about the brand (consumer-based brand equity, hereafter "CBBE") and based on choice or share in the marketplace (sales-based brand equity, hereafter "SBBE").

The rationale for perceptual measures is that brand equity resides in the hearts and minds of consumers. Academics have proposed systems of constructs to measure CBBE. The most notable amongst them are Aaker's Brand Equity Ten (Aaker 1996) and Keller's (1993) CBBE system that later evolved into the CBBE Pyramid (Keller 2001). Over the years, several market research and consulting companies have developed their own CBBE constructs and measures. Some examples are Young & Rubicam's Brand Asset Valuator (BAV), YouGov's Brand Index, the Beliefs part of Millward Brown's Brand Dynamics, Harris Interactive's EquiTrend, the Attitudinal Equity component of IPSOS's Brand Value Creator, and the Equity Engine model of Research International (now part of TNS). These systems use large scale consumer surveys to measure perceptions of brands along several dimensions. While each CBBE system has its own measures, they tap into many of the same or related dimensions, as pointed out by Keller (2001).

Sales-based measures of brand equity are marketplace manifestations of these consumer perceptions. In line with Keller's conceptualization, SBBE is the part of a brand's utility that comes on top of the contribution of its objectively measured attributes and marketing mix. SBBE is generally measured by the brand intercept in a choice or market share model, also referred to as the "residual" approach to measuring brand equity. It has been estimated from self-reported choices in conjoint and survey data (Park and Srinivasan 1994; Srinivasan, Park, and Chang 2005) and from actual brand choices and sales recorded in scanner data (Kamakura and Russell 1993; Sriram, Balachander, and Kalwani 2007). Importantly, Keller (1998) has pointed out that the extant measures do not include an important aspect of brand equity – enhanced consumer response to the brand's marketing mix.

Despite the importance of brand equity in marketing theory and practice, and the fact that firms spend considerable sums of money to track CBBE and SBBE, no empirical study to date has systematically investigated the link of CBBE with SBBE or with marketing mix response.

The goal in this paper is to fill that gap by addressing the following research questions:

1. What is the overall association between the major dimensions of CBBE and SBBE across product categories?
2. How do category characteristics moderate this association?
3. What is the association between the major dimensions of CBBE and consumer response to marketing mix variables of a brand?

We address these research questions with widely used measures of CBBE and SBBE for a large set of consumer packaged goods (hereafter CPG) brands over time. Specifically, we combine ten years of annual CBBE data from Brand Asset Valuator (BAV) with ten years of weekly Symphony IRI scanner data from which we estimate the intercept measure of SBBE as well as marketing mix elasticities. We conduct the analysis for a total of 290 brands across 25 CPG categories for which both SBBE and CBBE measures are available.

We document several findings that are new to the literature and important for marketing practice. We find that three of the CBBE dimensions – Relevance, Esteem, and Knowledge, which are highly correlated with one another – have a positive association with SBBE, whereas the fourth dimension – Energized Differentiation – has a small negative association with SBBE. The association is moderated by category characteristics. The effect of Relevance, Esteem, and Knowledge on SBBE is stronger in categories with more social value and more choice difficulty reflected in lower concentration. In contrast, Energized Differentiation leads to higher SBBE in more hedonic categories and in more concentrated categories. The pattern of association between CBBE and marketing mix response varies by CBBE dimension and by marketing variable. We find that Relevance, Esteem, and Knowledge are associated with stronger advertising, price promotion elasticities, and feature/display elasticities but with lower distribution elasticities.

Energized Differentiation is linked with stronger advertising elasticities but with weaker price promotion elasticities.

This analysis is important for both researchers and practitioners. Academic researchers use any of a variety of CBBE or SBBE measures that they happen to have access to, and, unless we have a good understanding of whether and how the different measures align, we have little idea whether the findings reported with one type of measure will hold up with another. Also, positive consumer perceptions are only useful to managers insofar as they translate into equity in the marketplace. As we will discuss later, both under- and over-achievement on SBBE compared to a brand's CBBE should be treated as red flags for further diagnosis and action. This analysis also provides guidance on which dimensions of CBBE managers should prioritize depending on the nature of the category. Finally, although conventional wisdom says that CBBE results in stronger marketing mix elasticities, prior research has not put that wisdom to a comprehensive empirical test (Keller and Lehmann 2006). Our findings regarding how the different dimensions of CBBE affect each of the major marketing mix elasticities are new to the academic literature and help managers in adjusting their marketing mix to leverage their CBBE.

Conceptual Background

Figure 1 presents the guiding conceptual framework for our research, as discussed next.

<Insert Figure 1 about here>

Measurement of CBBE

The CBBE measures that are compiled by industry sources cover a broad set of brands and categories and are based on large scale consumer surveys. A few have been used in academic studies. For instance, the *EquiTrend* measures have been related to stock performance, e.g., higher returns (Aaker and Jacobson 1994), lower idiosyncratic firm risk and cost of capital (Rego, Billett, and Morgan 2009), and better stock performance during the 2008 economic downturn (Johansson, Dimofte, and Mazvancheryl 2012). The *YouGov* measures have also been related to stock returns and idiosyncratic risk (Luo, Raithel, and Wiles 2013). The *BAV* measures, which we employ in this paper, have recently been used in a more wide-ranging set of studies. Mizik and Jacobson (2008) show that BAV measures are associated with unanticipated changes in stock returns after controlling for changes in accounting rates of return. Stahl, Heitmann, Lehmann, and Neslin (2012) examine the effect of these CBBE measures on customer acquisition, retention, and profit margin in the automobile industry. Lovett, Peres, and Shachar (2013) show how they drive offline and online word-of-mouth. Hence, past research has established the relevance of BAV's CBBE measures. It is the first and perhaps most widely used CBBE system, compiling the perceptions of tens of thousands of consumers each year on thousands of brands (bavconsulting.com).

Although BAV measures consumer perceptions on a large number of brand attributes, the company has identified four pillars – *Energized Differentiation*, *Relevance*, *Esteem*, and *Knowledg*e – as the key dimensions to track a brand's equity, in addition to an overall *Brand Asset* score.[1] Variants of these dimensions exist in most other CBBE systems as well. The specific measures used by BAV are provided in Web Appendix A. We will examine how these dimensions are associated with SBBE and with marketing mix response.

Energized Differentiation primarily measures a brand's uniqueness and ability to stand out from competition, but also its ability to meet future consumer needs. Differentiation is something that marketers invariably strive for (e.g., Kotler and Keller 2015; Moon 2010). As Stahl et al. (2012, p. 47) note, it is the "mantra of marketing."

Relevance measures how appropriate a brand is for consumers and how much it fits into their lives. It is viewed by BAV as the source of a brand's staying power (Mizik and Jacobson

2008). Keller (2001) equates it to consumer consideration in his CBBE pyramid and Aaker (2012) writes that becoming indispensably relevant in a category with "must have" characteristics and simultaneously making competitors irrelevant is a brand's route to growth.

Esteem measures how much people like the brand and hold it in high regard. Keller (2001) views it as positive quality and credibility perceptions. Similarly, quality and leadership are an important part of Aaker's (1996) Brand Equity Ten measures. BAV encompasses both quality and popularity within Esteem and views it as third in the progression of a brand's development, after Energized Differentiation and Relevance.

Knowledge measures consumers' awareness and understanding of what the brand stands for. Importantly, it is not just awareness of the brand but of its identity, which is built from the brand's communications as well as from personal experience with the brand. BAV views it as the culmination of brand-building efforts, and, in line with that view, Keller (2001) associates it with brand resonance at the pinnacle of the CBBE pyramid.

Measurement of SBBE

There is a long and well-established tradition in the literature of measuring SBBE as the brand intercept in a choice or market share model (e.g., Srinivasan 1979; Kamakura and Russell 1993). Some models provide individual-level SBBE estimates (Rangaswamy, Burke, and Oliva 1993; Park and Srinivasan 1994), but those are often based on conjoint or other survey-based data. Others use scanner panel choice data to provide segment-level estimates (Kamakura and Russell 1993), or store or market sales data to provide aggregate estimates (Sriram, Balachander, and Kalwani 2007; Goldfarb, Lu, and Moorthy 2009).

Since the goal of this research is to assess the association between the most widely used CBBE and SBBE measures in a generalizable and externally valid way, we use national data for a large number of categories and estimate SBBE as brand-specific intercepts in a market share attraction model. The model, which we describe in detail later, specifies a brand's attraction as a function of its physical attributes, marketing mix, and other control variables.

We next present our expectations about the association between CBBE and SBBE, about the category factors that moderate this association and about the link between CBBE and marketing mix elasticities. Table 1 summarizes these expectations in the form of numbered propositions that are referred to throughout the discussion.

< Insert Table 1 About Here >

Association between Consumer-Based Brand Equity and Sales-Based Brand Equity

Brands with high CBBE are more likely to get selective attention from consumers, be included in their consideration sets, be evaluated positively, and be chosen at the point of purchase (Hoeffler and Keller 2003). Hence, we expect a positive association between CBBE and SBBE overall, but not all the dimensions of CBBE may be equally associated with SBBE. Brands that rate high on Relevance, Esteem, and Knowledge have succeeded in developing a broad and deep appeal among consumers. These are the brands that many consumers believe are personally appropriate to them, think highly of, and understand well. Therefore, we expect that these three CBBE dimensions should be associated positively with SBBE (Proposition P1 in Table 1). Among the three, Relevance is closely associated with brand penetration, and Knowledge represents the pinnacle of CBBE. Therefore, we expect these two dimensions to be most strongly associated with SBBE.

The argument is different for Energized Differentiation. This CBBE dimension captures uniqueness and distinctiveness from other brands. But, as Stahl et al. (2012) note, this uniqueness may appeal strongly to some consumers but may not be to the liking of others. Indeed, Stahl et al. (2012) find a negative effect of this dimension on customer acquisition and retention in the automobile industry. Also, the discrepancy hypothesis in psychology suggests that consumers like new things that are sufficiently different from familiar ones, but not if they are too different (Haber 1958; see Miller, McIntyre, and Mantrala 1993 for an example). Thus, although Energized Differentiation may generate word-of-mouth, especially online (Lovett, Peres, and Shachar 2013), and garner higher prices and margins (Stahl et al. 2012), we expect it is associated with lower levels of SBBE (P2).

Category Moderators of the Association between CBBE and SBBE

Consumers use strong brands as diagnostic cues to reduce risk and uncertainty and to obtain social and emotional benefits from their choices. However, as these risks and benefits are not equally important across product categories, the brand is not equally relevant to consumers' decision process in different categories (Fischer, Völckner and Sattler 2010). We expect that CBBE should be more strongly associated with SBBE in categories where the brand is more relevant. In particular, the association should be stronger in categories with (a) more serious negative functional consequences of making the wrong choice; (b) higher information cost of making a choice, and therefore higher need to simplify choice; (c) higher symbolic or social value of the choice; and (d) higher experiential benefit from consumption (Fischer, Völckner and Sattler 2010; Laurent and Kapferer 1985; Steenkamp and Geyskens 2014). In line with these different roles that brands fulfil, we examine four category characteristics that may moderate the link between CBBE and SBBE.

Functional Risk: This is the consumer's subjective assessment of the risk that the product will not do its job if he/she makes the wrong choice in a category (Steenkamp and Geyskens 2014). The risk may be higher in some categories because the consequences of the wrong choice are perceived to be more serious (e.g., diapers or deodorant) or because there are stronger quality differences among products in the category (e.g., coffee). Other categories have less functional risk because differences in quality are not that consequential. For categories with higher functional risk, there is more at stake and consumers' choices are more influenced by the brand's promise (Erdem, Swait, and Louviere 2002; Fischer, Völckner and Sattler 2010). Hence we expect that CBBE will especially translate into SBBE for such categories. We expect that Relevance, Esteem and Knowledge will translate into SBBE more positively for high functional risk categories because these dimensions make the brand a familiar and appropriate choice (P1.1). However, differentiated brands can be perceived as risky. If a brand is really strong and differentiated on one aspect, the implication for consumers can sometimes be that it is not as good on other aspects (e.g., Keller, Sternthal, and Tybout 2002; Raghunathan, Naylor, and Hoyer 2006). Therefore, we expect Energized Differentiation is less likely to translate into SBBE for high functional risk categories (P2.1).

Category Concentration: Brands serve as a way to simplify choice and reduce the information costs associated with choosing among a broad array of alternatives (Erdem and Swait 1998; Keller and Lehmann 2006). The concentration of a category reflects the array of alternatives most consumers choose from. When concentration is low, consumers are faced with many, smaller brands; they need cues to facilitate decision making in such crowded categories. Brands with high Relevance, Esteem and Knowledge provide these cues and can stand out in a crowded field. Hence we expect these three dimensions to be more positively associated with SBBE in less concentrated categories (P1.2). Conversely, consumers face a more manageable choice set in highly concentrated categories. They can compare alternatives more deliberately and extensively, which makes a brand's uniqueness a more decisive factor in choice. Hence we expect that higher category concentration will enhance the impact of Energized Differentiation on SBBE (P2.2).

Social Value: One reason that consumers choose strong brands is because of their symbolic or social value (Fischer, Völckner and Sattler 2010; Laurent and Kapferer 1985; Steenkamp and Geyskens 2014). Social value may be higher in categories that are more visible to others (e.g., cigarettes) or are more often shared with others (e.g., beer). Consumers are more likely to value strong brands in categories that are high in social value, so higher levels of CBBE should more readily translate into SBBE in such categories (P1.3 and P2.3). We expect this positive moderating effect to hold especially for brands high on Esteem, Relevance and Knowledge because these brands are more likely to be recognized and respected by others.

Hedonic Categories: Consumers also derive emotional value and enjoyment from brands. This is more important in hedonic categories, which are evaluated, chosen, and consumed primarily based on their sensory attributes and overall image rather than on individual, physical, attributes (Holbrook and Hirschman 1982; Voss, Spangenberg, and Grohmann 2003). Consumers process hedonic categories more holistically and therefore may rely on cues such as the brand (Melnyk, Klein, and Völckner 2012). Accordingly, we expect the association of CBBE with SBBE to be stronger in hedonic categories (P1.4 and P2.4). Among the CBBE dimensions, we expect that the impact of Energized Differentiation on SBBE will be particularly enhanced in hedonic categories, because differentiation allows brands to capitalize on the unique and personal multisensory sensations they offer.

<u>Link between CBBE and Marketing Mix Response</u>

As we noted previously, brand equity refers not only to consumer preferences and choice but also to more favorable marketing response. Hoeffler and Keller (2003) synthesize the theoretical and conceptual mechanisms by which strong brands can get differential response to their marketing activities. Empirically, some researchers have examined whether brands with higher revenue premiums get better response to coupons and distribution (Slotegraaf, Moorman, and Inman 2003), price cuts (Ailawadi, Lehmann, and Neslin 2003), or have greater long-term promotion effectiveness (Slotegraaf and Pauwels 2008). Other work has studied how attitudinal metrics such as awareness and consideration mediate the effect of marketing actions on sales (Hanssens et al. 2014). However, none of them have studied the impact of CBBE dimensions on response to the major marketing mix variables at a brand's disposal – regular price, promotional price discount, feature/display activity, advertising, and distribution.

Price elasticity. Higher brand equity is expected to be associated with weaker price elasticity (e.g., Sivakumar and Raj 1997; Erdem, Swait, and Louviere 2002). On the other hand, high share or high quality brands tend to get a stronger response to price discounts (e.g., Blattberg and Wisniewski 1989; Sethuraman 1996). These studies highlight the importance of distinguishing between response to regular price changes and promotional price discounts. High CBBE brands are expected to be less sensitive to regular price changes over time and hence have lower (less negative) *regular* price elasticities. We expect that this holds for high Relevance, Esteem and Knowledge (P3) and for high Energized Differentiation (P4).

However, high CBBE brands have a bigger pool of potential customers that can be attracted with their promotional price discounts. This especially applies for brands high on Knowledge, Relevance and Esteem, reflecting their strong and broad appeal. Those brands are expected to be associated with stronger (more negative) promotion price elasticities (P5). However, as we noted earlier, brands with high Energized Differentiation appeal only to specific segments. Other segments may not be persuaded to buy even on price promotion (P6).

Feature/Display elasticity. Following the same logic, brands high on Knowledge, Relevance and Esteem have a bigger potential pool of customers to attract through features and displays, leading to a stronger elasticity for these activities (P7). Conversely, features and displays will be less of a draw for highly differentiated brands (P8).

Distribution elasticity. For distribution, the prediction is less clear cut. Certainly, strong brands have high distribution, but what are the returns to that distribution? Additional distribution points allow consumers to act on their preference to buy and more consumers prefer high equity brands. This suggests a stronger distribution elasticity for high equity brands. However, a hallmark of strong brands is consumers' willingness to search for them. If consumers search for these brands and already buy them wherever they are available or switch to whichever flavors, sizes etc. a retailer stocks rather than buying a less preferred brand, then returns to additional distribution will be lower (Farris, Olver, and De Kluyver 1989). Hence, we do not predict *a priori* whether brands with high Relevance, Esteem and Knowledge have a stronger or weaker distribution elasticity (P9).

Brands with high Energized Differentiation appeal to certain but not all consumers. These consumers already search for and buy these brands. Other segments may not be persuaded to buy these brands even with greater availability, reflected in a lower distribution elasticity (P10).

Advertising elasticity. Brand equity is expected to make a brand's advertising efforts more effective because consumers pay more attention to, react more positively to, and retain more information from the brand's marketing (Hoeffler and Keller 2003). This means that a brand's advertising efforts are more salient and impactful, and hence CBBE should be associated with higher advertising elasticities. We expect this to be the case for brands with high Relevance, Esteem and Knowledge (P11).

Although a smaller pool of consumers for brands with high Energized Differentiation suggests weaker advertising response, differentiated brands have unique selling propositions that can be effectively communicated through advertising. They may also be less prone to the interference that has been shown to hurt consumer memory of brands with a large number of associations (Meyers-Levy 1989), and hence we expect that these brands have stronger advertising elasticities (P12).

Data

Sample

We analyze a large set of CPG brands across 25 product categories in the US. Annual data on the four CBBE dimensions are provided by BAV Consulting. Weekly store level scanner sales data to estimate SBBE and elasticities are obtained from the IRI Marketing Science dataset (Bronnenberg, Kruger, and Mela 2008). Monthly advertising (traditional media and online) are obtained from Kantar Media. A consumer survey is conducted on Amazon's MTurk to obtain the three perceptual category characteristics (functional risk, social value, hedonic nature).

The IRI data span the period from 2001 to 2011 while the BAV data span the period from 2002 to 2012, so the empirical analysis covers the ten-year overlap period from 2002 to 2011. The sample selection is as follows. We start with all categories in the IRI dataset except for toothbrushes and photo film.[2] We select the subcategories that comprise substitutable products and that are covered throughout the ten-year period. We separate ketchup and mustard, two condiment types, as two categories. We merge razors with blades and frozen dinners with frozen pizza as many of the same brands are in both categories.

Next, we define and select brands in each category. Although the UPC description file in the IRI dataset has a field for the brand name, that field is rather narrow. For example, it has separate values for Folgers, Folgers Café Latte, Folgers Coffee House, Folgers Select, and several other variants of Folgers coffee, whereas BAV tracks Folgers Coffee as a whole. Therefore, we first code all the variants of each brand in each category into their parent brand.[3] In most cases this coding is consistent with BAV's brand definition. In the instances where BAV's definition is more disaggregate, we follow that, e.g., in separating Coke from Diet Coke and Budweiser from Bud Light. We rank brands according to their market share, and include those that jointly account for at least 90% of category sales. Further, we delete brands with less than two years of consecutive data and categories with fewer than three brands. This results in 441 brands across 25 categories. BAV data are available for 290 of these brands (see Table 2).

<Insert Table 2 About Here>

We note that some brands exist in multiple CPG categories, having expanded from their primary category (e.g., Kraft cheese) into additional ones (e.g., Kraft mayonnaise). Similarly, some brands have expanded into CPG categories from outside the grocery channel (e.g., Starbucks coffee). Consequently, the CBBE measures for these brands reflect equity built in their primary markets, while the SBBE measures reflect equity built in secondary markets into which they have extended. We flag all such cases with a Secondary Market indicator variable, so that this can be controlled for in the empirical analysis.

<u>Category characteristics</u>

Market concentration is operationalized as the total share of the top four brands in the category and is computed from the IRI data (Tirole 1988). For the remaining three moderators, which are perceptual constructs, we conducted an online survey of 752 US respondents on MTurk. Respondents first indicated how often they made a purchase in each of the 25 categories and then rated all categories they had purchased at least once in the past two years on two of the three constructs. To avoid overburdening respondents, we used two items per construct (details are in Web Appendix B). Table 2 includes means of the category characteristics.

Method

We obtain SBBE and marketing mix elasticities for each brand in each category using a market share model estimated with IRI data. Then we examine the association of the four dimensions of CBBE with SBBE, test for the moderating effect of the four category characteristics, and study the link between CBBE and marketing mix elasticities.

Market Share Model Specification

We use a multinomial logit (MNL) attraction model for market share (Cooper and Nakanishi 1988; Fok, Franses, and Paap 2002). The model is estimated for each of the 25 categories, using data aggregated up to the national brand-week level. The attraction model has several benefits. It is easily linearized and estimated; it is logically consistent with market shares between 0 and 1 and adding up to 1; and it captures cross effects between brands. It is an aggregate analog of the individual brand choice model from which SBBE can be estimated as the time-varying brand-specific intercept.

We expand this model in several ways to obtain valid estimates of SBBE and marketing mix elasticities. We include both the physical search attributes of a brand and its marketing mix variables as explanatory variables (Goldfarb, Lu, and Moorthy 2009; Kamakura and Russell 1993; Sriram, Balachander, and Kalwani 2007). Hence, the brand-year-specific intercept reflects the attraction attributable to the brand name after controlling for these observables, i.e., SBBE.

We use the differential-effects version of the MNL model, allowing not only the intercept but also the marketing mix coefficients to be brand specific. Also, brands may strategically set their marketing mix in response to unobserved demand shocks. In particular, they may respond to anticipated season-induced changes in demand. Although seasonal effects are more likely to occur in sales data than in market share data, we use quarterly dummies with brand-specific coefficients, to mitigate this source of endogeneity.

We also control for potential endogeneity due to other unobserved shocks, using Gaussian Copulas that directly model the joint distribution of the potentially endogenous regressors and the error term through control function terms (Park and Gupta 2012). The copula method does not require instrumental variables, and hence is particularly useful when valid instruments are hard to find (Rossi 2014). That is the case in our setting, where we have five potentially endogenous marketing mix variables measured at the national level for more than 400 brands from 25 categories. With a normally distributed error term, an identification requirement for the Gaussian Copula method is that the endogenous regressors are not normally distributed. In our application, Shapiro-Wilk tests at $p < .10$ confirm this for 99% of the cases.

We estimate the smoothing constant for advertising stock, which we define below along with all the other model variables. Finally, we account for serial correlation by applying the Prais-Winsten correction (Greene 2012). Thus, the complete model for the M brands (where M can vary over time to accommodate brand entry or exit) in each category is as follows:

$$\mathrm{MS_{bt}} = \frac{\mathrm{A_{bt}}}{\sum_{\mathrm{j=1}}^{\mathrm{M}} \mathrm{A_{jt}}} \tag{1}$$

$$\begin{aligned}\mathrm{A_{bt}} = \exp\Big(&\textstyle\sum_{\mathrm{y \in Y_b}} \alpha_{\mathrm{by}} \cdot \mathrm{DumYear_{ty}} + \beta_{\mathrm{b1}}\mathrm{RegPrice_{bt}} + \beta_{\mathrm{b2}}\mathrm{PriceIndex_{bt}} + \\ &\beta_{\mathrm{b3}}\mathrm{FD_{bt}} + \beta_{\mathrm{b4}}\mathrm{Distr_{bt}} + \beta_{\mathrm{b5}}\mathrm{AdStock_{bt}} + \textstyle\sum_{\mathrm{a,l}} \gamma_{\mathrm{al}}\mathrm{Attr_{bal}} + \\ &\textstyle\sum_{\mathrm{q=2}}^{4} \kappa_{\mathrm{bq-1}}\mathrm{Quarter_{qt}} + \sum_{\mathrm{k}} \omega_{\mathrm{kb}}\mathrm{Copula_{kbt}} + \varepsilon_{\mathrm{bt}}\Big)\end{aligned} \tag{2}$$

where we drop the category index c to simplify exposition and:

$\mathrm{MS_{bt}}$ = Unit market share of brand b in week t;

$\mathrm{A_{bt}}$ = Attraction of brand b in week t;

α_{by} = Brand- and year-specific intercept for brand b in year y;

$DumYear_{ty}$ = Indicator variable, equal to 1 if week t is part of year y, 0 otherwise;

$RegPrice_{bt}$ = Regular price of brand b in week t, deflated by the appropriate Consumer Price Index to account for category-wide price changes;

$PriceIndex_{bt}$ = Actual price of brand b in week t divided by its regular price to measure its promotional price discount;

FD_{bt} = Intensity of feature and/or display support for brand b in week t;

$Distr_{bt}$ = Total distribution of the Stock Keeping Units (SKUs) of brand b in week t;

$AdStock_{bt}$ = Smoothed advertising spending or Advertising Stock of brand b in week t where $AdStock_{bt} = \lambda\, AdStock_{b,t-1} + (1-\lambda)\, Advertising_{bt}$;

$Attr_{bal}$ = Fraction of the SKUs of brand b that have attribute level l for attribute a;

$Quarter_{qt}$ = Quarterly dummy for quarter q = 1 if week t is in quarter q, 0 otherwise, and mean-centered at the brand level;

$Copula_{kbt}$ = Gaussian copula (control function term) for marketing mix variable k of brand b in week t to control for potential endogeneity of the variable; and

ε_{bt} = Normally distributed error term for brand b in week t.

The market shares, attributes, and marketing mix variables in the model are aggregated up to the national brand-week level from store-level SKU data. The aggregation procedure and the variable operationalization are in Web Appendix C. We note that the model distinguishes between regular and promotional price through two separate variables, RegPrice and PriceIndex respectively. FD captures the additional effect of feature/display support over and above the impact of a promotional price discount. The Distr variable measures the percentage of SKUs on the shelf that belong to the brand, thus incorporating both distribution breadth and the depth of the product line in distribution. The number of attribute variables differs across categories as the number of attributes and the levels of each attribute varies (for details, see Web Appendix D). The Gaussian copula for each marketing variable X_{bt}, for brand b in week t is: $\mathrm{Copula}_{bt} =$

$\Phi^{-1}(H(X_{bt}))$, where Φ^{-1} is the inverse distribution function of the standard normal, and $H(\cdot)$ is the empirical cumulative distribution function of X_b. Finally, the brand-year intercepts measure SBBE, and are estimated for all years Y_b for which data on brand b are available.

<u>Model Estimation</u>

The attraction model for a category can be written as a system of M equations. Because shares add to one, the dependency across equations reduces the rank of the system to M-1. For estimation, the system can be normalized by geometric mean-centering (Cooper and Nakanishi 1988), or with respect to a base brand (Bronnenberg, Mahajan and Vanhonacker 2000). Both approaches are mathematically equivalent, and we use the latter for computational ease (Fok, Franses, and Paap 2002).

To linearize model (1), we take its logarithm for each of the M brands. Next, we subtract a base brand B from both sides of each of the other M-1 equations. The base brand is selected as the brand with the most observations. We estimate this system of M-1 seemingly unrelated equations for each category using Feasible Generalized Least Squares (FGLS):

$$\begin{aligned}\log\left(\frac{MS_{bt}}{MS_{Bt}}\right) &= \sum_{y\in Y_b}(\alpha_{by}-\alpha_{By})\cdot DumYear_{ty} + \beta_{b1}RegPrice_{bt} - \beta_{B1}RegPrice_{Bt} + \\ &\beta_{b2}PriceIndex_{bt} - \beta_{B2}PriceIndex_{Bt} + \beta_{b3}FD_{bt} - \beta_{B3}FD_{Bt} + \beta_{b4}Distr_{bt} - \\ &\beta_{B4}Distr_{Bt} + \beta_{b5}AdStock_{bt} - \beta_{B5}AdStock_{Bt} + \sum_{q=2}^{4}\kappa_{bq-1}Quarter_{qt} + \\ &\sum_{a,l}\gamma_{al}(Attr_{bal} - Attr_{Bal}) + \sum_k(\omega_{kb}Copula_{kbt} - \omega_{kB}Copula_{kBt}) + \varepsilon_{bt} - \varepsilon_{Bt}.\end{aligned} \tag{3}$$

The yearly intercepts for the base brand (α_{By}) are normalized to zero for identification. To back out SBBE for the base brand, we use the assumption of the attraction model that the total attraction across brands is constant over time, leading to brand b's SBBE in year y:

$$SBBE_{by} = \begin{cases}\frac{1}{M}\left(\alpha_{by}(M-1) - \sum_{b'\neq b}\alpha_{b'y}\right) & \text{if } b \neq B \\ -\frac{1}{M}\sum_b \alpha_{by} & \text{if } b = B\end{cases} \tag{4}$$

We compute the corresponding standard errors using the delta method.

To select the advertising smoothing constant λ for the AdStock variable, we use a grid search on the interval [0, .9] in increments of .1 that yields the best likelihood. As equation 3 shows, all other parameters in the system of equations are directly estimated, including the brand-specific marketing mix response coefficients. From these coefficients, we compute each brand's marketing mix elasticities as follows (Cooper and Nakanishi 1988, p. 33):

$$\eta_{Xb} = \frac{\partial MS_{bt}}{\partial X_{bt}} \frac{X_{bt}}{MS_{bt}} = \beta_b (1 - \overline{MS_b}) \overline{X_b}, \tag{5}$$

where $\overline{MS_b}$ and $\overline{X_b}$ are brand b's average market share and marketing instrument X, respectively.

<u>Second-stage Analysis for the CBBE-SBBE link and the CBBE-Elasticity Link</u>

We estimate the market share model across all brands to ensure good coverage of each category and valid estimates of SBBE and marketing elasticities. After estimating this model, we run a second-stage analysis to test the link between the SBBE and elasticity estimates on the one side and CBBE on the other side. We use the estimates from eq. (4) and eq. (5) as dependent variables and regress them on CBBE and other relevant covariates (more details are given below). In the second-stage analysis, we use WLS to account for the uncertainty in the SBBE and elasticity estimates from the first stage. We also use conservative clustered standard errors to account for the fact that each brand contributes multiple observations to the SBBE model. This two-stage approach is in line with an established tradition in the marketing literature (e.g., Nijs et al. 2001; Srinivasan et al. 2004; Steenkamp et al. 2005).[4]

Results

<u>Market Share Model Estimates</u>

Table 3 summarizes the marketing mix elasticities obtained across the 441 brands in 25 product categories. The weighted averages of the elasticities have the expected signs and their meta-analytic Z-statistics (Rosenthal 1991) are significant. The relative magnitudes of the mean regular price elasticity (-.79) and the promotional price elasticity (-2.59) are in line with meta-analytic results (Bijmolt, van Heerde, and Pieters 2005). The mean Feature/Display elasticity is significant though it appears small (.02). Note, however, that this effect is over and above the effect of promotional price cuts which are captured by the price index variable. The mean advertising elasticity equals only .001, consistent with prior research (Sriram, Balachander, and Kalwani 2007; Sethuraman, Tellis, and Briesch 2011; Van Heerde et al. 2013). In Web Appendix E, we summarize elasticity estimates and advertising smoothing constants λ by category.

<Insert Table 3 About Here>

Previous research (Ataman, Van Heerde, and Mela 2010) has reported higher elasticities for distribution breadth than ours (.40), but we note that their measure of distribution is %Product Category Volume (PCV) whereas we use a brand's total distribution (Web Appendix C). Total distribution elasticity is expected to be lower than the elasticity for Brand PCV because an increase in a brand's total distribution often adds SKUs to an existing assortment in stores, some of the sales of which are cannibalized from existing SKUs of the brand. On the other hand, an increase in %PCV adds stores that previously did not stock any SKUs of the brand.

Overall, therefore, the elasticities have face validity and are consistent with prior research. We note that the copula correction terms are statistically significant in 70% of the cases (1427 out of 2046 at $p<.10$), underscoring the importance of dealing with endogeneity.

The Association between CBBE and SBBE

Figure 2 shows the association between CBBE and SBBE in the most recent year of the data (2011) for two categories with a large number of brands – beer and laundry detergent. Beer is more hedonic and high on social value, while detergent is less hedonic and high on functional risk. To provide a general overview, Figure 2 uses BAV's composite Brand Asset score for CBBE; we will examine its dimensions in detail below. In this and subsequent analyses, measures are standardized across brands in each category to allow comparability. To underscore the difference between a brand's SBBE and its market share, Figure 2 also plots the Brand Asset score against market share.

< Insert Figure 2 About Here >

Figure 2 illustrates the coverage of the data, the overall positive association between CBBE and SBBE, and the face validity of various brand positions. Several well-known brands achieve high scores on both CBBE and SBBE, e.g. Budweiser and Bud Light for beer, and Tide and Arm & Hammer for laundry detergents. Others, like Bass Ale and Surf score low on both CBBE and SBBE. We also note that the highest market share brands are not necessarily the ones with the highest SBBE, a point to which we will return shortly.

<Insert Table 4 About Here>

Correlations. Table 4 shows correlations between the SBBE and CBBE measures across the 2423 brand-year observations in the sample. As expected, the pattern of association of CBBE dimensions with SBBE is bifurcated, with three dimensions – Relevance, Esteem, and Knowledge – showing a similar pattern and Energized Differentiation showing a very different pattern. In line with proposition P1, we find moderate positive correlations (ranging between .35 and .53) of SBBE with the first three CBBE dimensions. Energized Differentiation has a small negative correlation with SBBE (-.14), in line with P2.

The CBBE dimensions have more positive correlations with market share than they do with SBBE. For instance, Relevance and Esteem have correlations of .56 and .55 with market share. This finding makes sense. SBBE is the "residual" attraction of a brand after controlling for its physical attributes, its marketing mix, and its marketing mix response, whereas market share is the joint result of all these elements. To the extent that high CBBE brands are of higher quality, have a more attractive marketing mix, and have stronger response to it, CBBE should be more positively associated with market share than with SBBE.

Principal Component Analysis. Before we estimate the second-stage models, we need to account for the high correlations between some of the CBBE dimensions that could cause multicollinearity. Therefore, we conduct a principal component analysis to reduce them to a smaller number of orthogonal components. We extract the two principal components with eigenvalues greater than one, capturing 89% of the variance in the four dimensions. As the correlation pattern in Table 4 suggests, the first component has very high loadings of Relevance (.93), Esteem (.95) and Knowledge (.88), and a low loading of Energized Differentiation (.02). In line with Mizik and Jacobson (2009), we name this component "Relevant Stature" (RelStat). The second CBBE component has a very high loading of Energized Differentiation (.99) and low loadings of Relevance (.14), Esteem (.07) and Knowledge (-.11), and we label it "EnDif". We use these principal component scores in the rest of the analysis.[5]

Category Moderators of the Association between CBBE and SBBE

To test the link between the CBBE dimensions and SBBE and the moderating influence of the category characteristics, we regress SBBE on the two CBBE principal components, the four category characteristics, and their interactions with the CBBE components. In addition, we use the Secondary Market indicator variable to account for brands that have extended into new domains from the ones where their CBBE is built, as discussed earlier. A benefit of such extensions is that firms can leverage their brand equity instead of building it from scratch in a new market. However, the SBBE for brands operating in – from their perspective – secondary categories is likely to be lower than would be expected based on the CBBE in their primary categories. Therefore, we expect this variable to have a negative coefficient.

The regression model for SBBE of brand b in year y is:

$$\begin{aligned}\mathrm{SBBE_{by}} = {} & \delta_0 + \delta_1\mathrm{RelStat_{by}} + \delta_2\mathrm{EnDif_{by}} + \delta_3\mathrm{RelStat_{by}}\times\mathrm{C4_c} + \delta_4\mathrm{EnDif_{by}}\times \\ & \mathrm{C4_c} + \delta_5\mathrm{RelStat_{by}}\times\mathrm{Hed_c} + \delta_6\mathrm{EnDif_{by}}\times\mathrm{Hed_c} + \delta_7\mathrm{RelStat_{by}}\times\mathrm{FuncRisk_c} + \\ & \delta_8\mathrm{EnDif_{by}}\times\mathrm{FuncRisk_c} + \delta_9\mathrm{RelStat_{by}}\times\mathrm{Social_c} + \delta_{10}\mathrm{EnDif_{by}}\times\mathrm{Social_c} + \\ & \delta_{11}\mathrm{SecMkt_b} + \delta_{12}\mathrm{C4_c} + \delta_{13}\mathrm{Hed_c} + \delta_{14}\mathrm{FuncRisk_c} + \delta_{15}\mathrm{Social_c} + \mathrm{u_{by}}.\end{aligned} \tag{6}$$

where RelStat and EnDif are the two CBBE principal components, C4 is Category Concentration, Hed is the perception of how hedonic the category is, FuncRisk is the perceived functional risk of the category, Social is the perceived social value of the category, and SecMkt is the dummy variable for whether the brand is in a secondary domain.

We mean-center the category characteristics so that the coefficients of the CBBE principal components can be interpreted as their effects at average values of category characteristics. Because $\mathrm{SBBE_{by}}$ is an estimated parameter, we use Weighted Least Squares (WLS) to estimate equation 6. The weight is the inverse of the standard error of $\widehat{\mathrm{SBBE}}_{\mathrm{by}}$ divided by its standard deviation to account for the standardization applied by category. We use robust clustered standard errors since there are multiple observations per brand.

Table 5 shows the model results. The CBBE components and category moderators explain 47% of the variance in SBBE, and most of the effects are consistent with the propositions in Table 1. Relevant Stature has a positive effect on SBBE ($\hat{\delta}$=.52, *p*<.01, P1 supported). This is enhanced by a category's social value ($\hat{\delta}$=.29, *p*<.10, P1.3 supported) but reduced for more concentrated categories ($\hat{\delta}$=-.50, *p*<.10, P1.2 supported). Thus, the greater the social signaling value of a category and the more fragmented it is, the more readily the status of a brand translates into SBBE. We also find that the more hedonic the category, the smaller the effect of Relevant Stature on SBBE ($\hat{\delta}$ =-.09, *p*<.05, P1.4 not supported). We do not find a significant role for the category's perceived functional risk (P1.1 not supported).

<Insert Table 5 About Here>

Energized Differentiation has a small significant negative main effect ($\hat{\delta}$=-.08, *p*<.05), P2 supported). However, there are two category characteristics with positive moderating effects. Energized Differentiation pays off more in terms of SBBE in more concentrated categories ($\hat{\delta}$=.72, *p*<.01, P2.1 supported), in line with the argument that if a category has a few big brands, consumers can better ascertain and appraise a brand's unique aspects. Energized Differentiation also has a more positive SBBE effect for more hedonic categories ($\hat{\delta}$=.13, *p*<.01, P2.4 supported), consistent with the notion that for these categories, consumers are better able to appreciate and hence choose unique brands. We do not find evidence for the moderating roles of functional risk and social value (P2.1 and P2.3 not supported).

Table 5 shows that brands that have extended into secondary domains have lower SBBE than what would be expected based on their primary market CBBE ($\hat{\delta}$=-.59, *p*<.01). The main effects of the category characteristics are not significant, which is to be expected because the dependent variable is standardized by category.

The Association between CBBE and Marketing Mix Elasticities

Table 6 shows the estimates from the WLS regression models for the five marketing mix elasticities. The explanatory variables are the two CBBE principal components: RelStat and EnDif. As before, all variables are standardized by category.

<Insert Table 6 About Here>

As expected (see Table 1), higher scores on Relevant Stature are associated with more positive advertising ($\hat{\delta}$=.07, *p*<.10, P11 supported), more positive feature/display ($\hat{\delta}$=.16, *p*<.01, P7 supported), and more negative promotional price elasticities ($\hat{\delta}$=-.14, p<.01, P5 supported). These findings confirm the notion that brands strong on Relevant Stature have a large pool of (latent) customers interested in buying the brand. Promoting the brand through advertising, price promotions and feature/display activity pays off for these brands. On the other hand, brands that are higher on Relevant Stature have lower distribution elasticities ($\hat{\delta}$=-.19, p<.01). Of course, such brands get the most distribution, but consumers are willing to go the extra mile to buy them, making gains in distribution less important, in line with Farris, Olver, and De Kluyver (1989).

Brands high on Energized Differentiation are in a very different position: their promotional price elasticity is weaker ($\hat{\delta}$=.09, p<.10, P6 supported). This result is in line with the idea that Energized Differentiation is rather associated with niche brands whose buyers are less-price sensitive. These brands do have a stronger advertising elasticity ($\hat{\delta}$=.08, p<.10, P12 supported), in line with having a clear value proposition to communicate.[6]

We do not find significant effects of the CBBE components on regular price elasticity (P3 and P4 not supported) nor a significant effect of Energized Differentiation on the feature/display or distribution elasticity (P8 and P10 not supported).

Discussion

Based on the national performance of 290 CPG brands in 25 categories across 10 years, we have examined the empirical association between CBBE and SBBE. Using widely accepted measures in the literature and in practice, we link the underlying dimensions of CBBE to not only brand-intercepts, but also to the effectiveness of five major marketing mix variables. We now discuss the main insights organized along key themes. Within each theme, we offer managerial implications and, if applicable, opportunities for future research. Table 7 provides an overview of the main findings.

<Insert Table 7 About Here>

Positive Association of CBBE with SBBE, but Energized Differentiation is Different

The link of SBBE with three of the four CBBE dimensions is positive and fairly strong. Thus, investments into CBBE pay off if they build consumers' awareness and understanding of what the brand stands for (Knowledge), make the brand appropriate to the consumer (Relevance), and enhance consumer regard for the brand (Esteem). Examples of the brands in this study that do very well on these three CBBE dimensions and on SBBE are Budweiser, Coke, Marlboro, Folgers, Secret, Lysol, Tide, and Doritos, to name a few. These brands have found a way to be very clear what they stand for, to be relevant across different segments of the market, and to be held in high esteem. Overall, Knowledge is the dimension that is most strongly correlated with SBBE. This provides generalizable empirical support for the conceptual proposition that building an understanding of what the brand stands for is the ultimate accomplishment for equity in the marketplace.

At the same time, we have also documented a small negative association between SBBE and the fourth CBBE dimension – Energized Differentiation – which reflects a brand's uniqueness compared to competitors and its agility to meet changing consumer demands. Hence, a strongly differentiated brand does not necessarily appeal to the masses. Specifically, the sample includes several niche-type brands that are low on Knowledge and high on Energized Differentiation, with relatively low SBBE. Many of these are fairly new, like Fat Tire and Blue Moon beer, Bear Naked cereal, Axe deodorant, Seventh Generation, and Method household cleaner. These products entered the market during the period of analysis or in the decade before it. They needed to be different to find a place in the market and several have not (yet) expanded beyond the niche in which they entered. As a result, their SBBE is low.[7]

However, high Energized Differentiation does not mean a brand has to be a niche player. Several mature brands in the sample, for example Dr Pepper, Coke, Special K, Lysol, Doritos, and Tide, do reasonably well on Energized Differentiation as well as the other CBBE dimensions and hence on SBBE. Presumably, the combination of CBBE dimensions gives these brands more staying power in the long term, though it also takes several years of consistent brand development to build up the combination.[8]

We have focused on the contemporaneous association between CBBE and SBBE. Future research could examine the dynamics of how current CBBE dimensions might drive future SBBE. We conducted some preliminary analysis and did not find any difference between contemporaneous and one- or two-year lagged effects. However, at least for new brands, Energized Differentiation in the early years may have a positive effect on SBBE in later years. There may also be dynamic effects among CBBE dimensions. For example, Energized Differentiation in the present may enhance Esteem in later years. Note, though, that brand equity is built over years, not weeks or months, so a long time unit of analysis and a much longer data period would be needed to assess the dynamics in its evolution.

Choice Complexity, Social, and Experiential Value Moderate Effect of CBBE on SBBE

Variation in the association between CBBE and SBBE across categories is explained by the extent to which brands serve as cues for simplifying choice, and provide social value and personal enjoyment. As before, patterns differ for Energized Differentiation versus the other three CBBE dimensions which we combine into Relevant Stature.

< Insert Figure 3 About Here>

The effect sizes can be seen from the spotlight analysis in Figure 3. Using the estimates (Table 5), we compute the effect of CBBE on SBBE for categories in the 10th versus the 90th

percentile of the distribution of category characteristics. The coefficients represent changes in SBBE measured in standard deviations due to a one standard deviation increase in CBBE. The effect of Relevant Stature on SBBE is substantially stronger for the 90th versus 10th percentile on social value (.63 versus .37); it is also considerably stronger for high versus low hedonic nature (.67 versus .41) and for low versus high concentration (.61 versus .35).

The spotlight analysis also demonstrates that Energized Differentiation can enhance SBBE in some circumstances. For highly hedonic categories, the effect is positive (.09). This is also the case for highly concentrated categories (.17).

These results offer guidance to brand managers on which CBBE dimensions to prioritize contingent on the category. For categories that have high social value (e.g., beer, cigarettes), are fragmented (e.g., frozen pizza and dinners) and/or less hedonic (disposable diapers), it especially pays off to focus on Relevant Stature instead of highlighting differences. The brand's positioning and communication should explain what the brand stands for (enhancing brand knowledge), make it relevant for many consumers and enhance its esteem. While Relevant Stature cannot be ignored, brands that are in hedonic (e.g., coffee) or concentrated categories (e.g., ketchup), or those with lower social value (e.g., mayonnaise, mustard) should highlight or enhance Energized Differentiation. As differences between brands are more appraisable in these categories, marketers must communicate the brand's unique selling points and their efforts to keep on meeting consumer's needs.

<u>Nuanced Effects of CBBE on Marketing Mix Elasticities</u>

The results on the association of CBBE with marketing mix elasticities caution against a broad-brush assumption that brand equity enhances all marketing mix response. Reality is more nuanced – both along the dimensions of CBBE, and across marketing mix elements. We find that relevant, well-known brands held in high esteem benefit more from price discounts and display/feature support. A spotlight analysis (see Figure 4) based on the model estimates in Table 6 illustrates that this impact is sizeable. For example, brands at the 90th versus 10th percentile on Relevant Stature average a price promotion elasticity of -3.32 versus -2.64, a 26% increase in magnitude; they also benefit from more positive advertising elasticities (.005 versus .001), though the magnitudes are small overall. Importantly, distribution elasticities are *smaller* for brands in the 90th versus the 10th percentile on Relevant Stature (.33 versus .59). High Relevant Stature brands get broad distribution but their marginal return on distribution is lower because consumers are willing to search for them. This result is not simply because such brands have reached a saturation point in distribution. We don't measure ACV or PCV weighted brand distribution which is indeed close to 100% for most big brands. Instead, we measure the weighted share of SKUs on the shelf, which is much lower even for the strongest brands. The implication is that high Relevant Stature brands should prioritize better promotional pass-through and feature/display support over additional SKUs on the shelf.

< Insert Figure 4 About Here>

In contrast, brands that excel in Energized Differentiation benefit relatively less from price promotions (-2.73 versus -3.13 for the 90th versus 10th percentile). They are better supported through their relatively effective advertising investments (.005 versus .001) and their marginally higher return on distribution (.49 versus .46). It is important for such brands to balance the pull and push sides of their marketing mix so that neither gets too far ahead of the other, especially because many of them are new and may have limited marketing budgets.

Important Insights in the "Misalignment" of CBBE

This research shows that (i) the dimensions of CBBE are not well-aligned; (ii) CBBE does not always align well with SBBE and (iii) CBBE aligns better with market share than with SBBE. The nature of these "misalignments" has important ramifications for academic research, for firms tracking brand equity, and for brand managers using these measures as diagnostic tools.

(i) Dimensions of CBBE. As we noted earlier, academic researchers use measures of brand equity in a variety of contexts like new product extensions, marketing mix, financial outcomes, and strategic brand alliances. Understandably, researchers are constrained by the availability of CBBE data. However, since different dimensions of CBBE and SBBE are likely to have very different effects on the phenomena of interest, our work implies that researchers should make and test more specific predictions related to the particular measures they use rather than rely on broad-based predictions related to brand equity. This research also cautions against combining very different measures into a composite brand equity score, as this may mask varying or even opposing effects of the underlying measures. Our analysis suggests that it is particularly important to track Energized Differentiation separately from the other dimensions.

(ii) CBBE vs SBBE. The fact that the alignment of CBBE with SBBE is strong but not perfect offers a diagnostic opportunity. New and important insights can emerge from outliers, not just from observations that are in line with the overall association between CBBE and SBBE. Figure 5 plots SBBE against CBBE for beer category in 2011, using a regression line and its 95% confidence interval for the mean. Brands above the confidence interval can be thought of as "over-achievers" because they garner significantly more SBBE than expected based on their CBBE. Conversely, brands below the confidence interval can be viewed as "under-achievers".

< Insert Figure 5 About Here >

A notable over-achiever is Corona, the Mexican beer brand that succeeds in the marketplace despite relatively poor taste ratings (Stock 2014). Its success has been attributed to a consistently advertised “sand, sun, and lime wedge” image. The challenge for an over-achiever such as Corona is to find out through marketing research why their relatively strong SBBE is not mirrored in a strong position in the hearts and minds of consumers (CBBE). Otherwise, the brand may not sustain its marketplace strength.

A notable under-achiever is Fat Tire, a brand that is highly differentiated and that began national distribution around 2002. Its position is in line with the pattern that newer brands tend to be under-achievers, because it takes time for the positive attitudes they build to percolate into marketplace choices. New brands should monitor the development of their SBBE over time and make sure they migrate upwards on the CBBE-SBBE plot. Tracking market share is not enough since that can be propped up with price cuts and other temporary tactics. Miller is also an under-achiever, but unlike Fat Tire, its position is not attributable to newness or to differentiation, making it a bigger cause for concern. Such an under-achiever must also research why their relatively favorable CBBE position does not manifest itself in SBBE – what is stopping consumers from acting in line with how they think and feel about the brand?

Our purpose is not to explain why specific brands are under- or over-achievers, but to illustrate the value of the analysis as a diagnostic tool. Irrespective of whether or not a marketer concludes that its place on the plot is a cause for concern, it is useful to compare each CBBE dimension with SBBE and, if a brand is significantly “off the line”, diagnose the cause for it.

(iii) CBBE vs SBBE vs Market Share. SBBE removes from a brand’s market share the effects of its objective attributes and marketing mix, so that a brand’s features and (possibly temporary) tactics do not confound its intrinsic equity. Obviously, when consumers choose brands, they take into account the whole package (SBBE + attributes + marketing mix), not just SBBE. Therefore, it is not surprising that CBBE aligns more strongly with market share than

with SBBE. Other researchers have argued that brand equity is also reflected in consumers' subjective perceptions of a product's experience attributes (Goldfarb, Lu, and Moorthy 2009; Park and Srinivasan 1994; Srinivasan, Park, and Chang 2005). Future research could separate the effects of "experience" from "search" attributes, and examine how CBBE affects perceptions of these different attribute types.

Some of the Brand Equity Associations Merit Further Examination

In this study, we tested several propositions on how CBBE links to SBBE, on how this link is moderated by category characteristics, and on how CBBE links to marketing elasticities. We find support for many of them, but the ones for which we do not deserve examination. There is only one case where we find a significant effect in the opposite direction than anticipated: the effect of Relevant Stature on SBBE is smaller for more hedonic categories. An explanation is that the more personally enjoyable a category is (which is more inward-looking), the less important are broad appeal and status for SBBE (which are more outward-looking).

For some other propositions, we do not find a significant effect. One intriguing null result is that functional risk does not strengthen the effect of relevant stature on SBBE, though Fischer, Völckner, and Sattler (2010) identified functional risk as a driver of brand relevance. An explanation is that their research examined vastly different categories ranging from CPG to electronics, retail stores, and automobiles whereas we study CPG categories with less variation in perceived functional risk.

Another interesting result is the lack of effect of CBBE on regular price elasticity. We anticipated that high CBBE brands would have lower regular price elasticities. However, high CBBE brands may face a relatively small loss in demand when their regular price increases, but a relatively strong gain in demand when their regular price decreases (Ailawadi, Lehmann, and

Neslin 2003). Our model assumes symmetric elasticities, but future research could allow for asymmetric effects. A final result worth investigating is the insignificant effect of Energized Differentiation on feature/display and distribution elasticities. Our expectations were based on the notion that differentiated brands mostly appeal to specific consumer segments, reducing the overall draw of feature/display and additional distribution. However, distribution and merchandising may, like advertising, make more consumers in those segments aware of the differentiated (and often new) brands.

Conclusion

No research is perfect, and ours is no exception. Future research can study refinements to our study to deepen the insights. For instance, we use aggregate scanner data to measure SBBE, as this matches the national level of the CBBE data. Future research could estimate less aggregate store- or market-level models and study geographical variation. We have examined one type of CBBE and one type of SBBE measure. While the measures we chose are arguably the most widely used in the literature, there is certainly value in examining others. In addition, future research could try to estimate an integrated model where the intercepts and response parameters of the market share model are specified as a function of (time-varying) CBBE measures while allowing for parameter heterogeneity and endogeneity. A Transfer Function Dynamic Hierarchical Linear Model could be suitable (Peers, van Heerde, and Dekimpe 2016).

Despite its limitations, this paper offers new insights into the strength and nature of the relationship between consumer-based and sales-based brand equity measures. The finding that these measures align quite well but not perfectly, and that there are important differences at the level of component parts, shows that there is room for important follow-up questions for both brand managers and academic researchers in this domain.

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Footnotes

[1] The original four pillars identified by BAV were differentiation, relevance, esteem, and knowledge. In their work with the company, Mizik and Jacobson (2008) then identified energy as a fifth pillar which has since been combined with differentiation as energized differentiation.

[2] We dropped toothbrushes and photo film because their sales volume is provided in *counts* without information on the number of toothbrushes in a package or the number of exposures in a roll of film.

[3] A file listing the IRI subcategories and IRI brands included in our analysis, along with our coding of their respective parent brands, is available for download under "Supplemental Material" at http://dx.doi.org/10.1509/jm.15.0340.

[4] A Hierarchical Linear (HLM) framework that models market shares in a first layer and explains the intercepts and response parameters in a second layer is theoretically more efficient. However, we have ten years of weekly data to estimate the brand-specific parameters with precision, so the potential efficiency advantage of HLM is likely to be small (Gelman 2005). Conversely, an HLM would have to deal with missing data in the second layer for the 151 out of 441 brands without BAV data. Replacing missings by zeros or averages, or using a missing data dummy would introduce biases since the missing data may not be random (Schafer and Graham 2002). Adopting a Bayesian data imputation approach would add substantial complexity. For these reasons, and because it accounts for uncertainty in the model estimates and for error dependencies, we believe the two-stage regression is preferable to HLM here.

[5] We also converted the principal component level results back to the level of the individual four CBBE dimensions (e.g., Rust, Lemon, and Zeithaml 2004). Those results are summarized in Web Appendix F.

[6] The category characteristics may moderate the effects of the CBBE components on elasticities (e.g., Erdem, Swait, and Louviere 2002). Although those are third order effects for which we do not have strong expectations, we did test them. Complete results are available in Web Appendix G.

[7] In fact, if we exclude these newer brands from the analysis, the association between Energized Differentiation and SBBE becomes insignificant.

[8] To test for any concurrent synergies, we included an interaction between Energized Differentiation and Relevant Stature in the regression of SBBE on CBBE components, but found that it was not statistically significant.

Figure 1

Guiding Framework

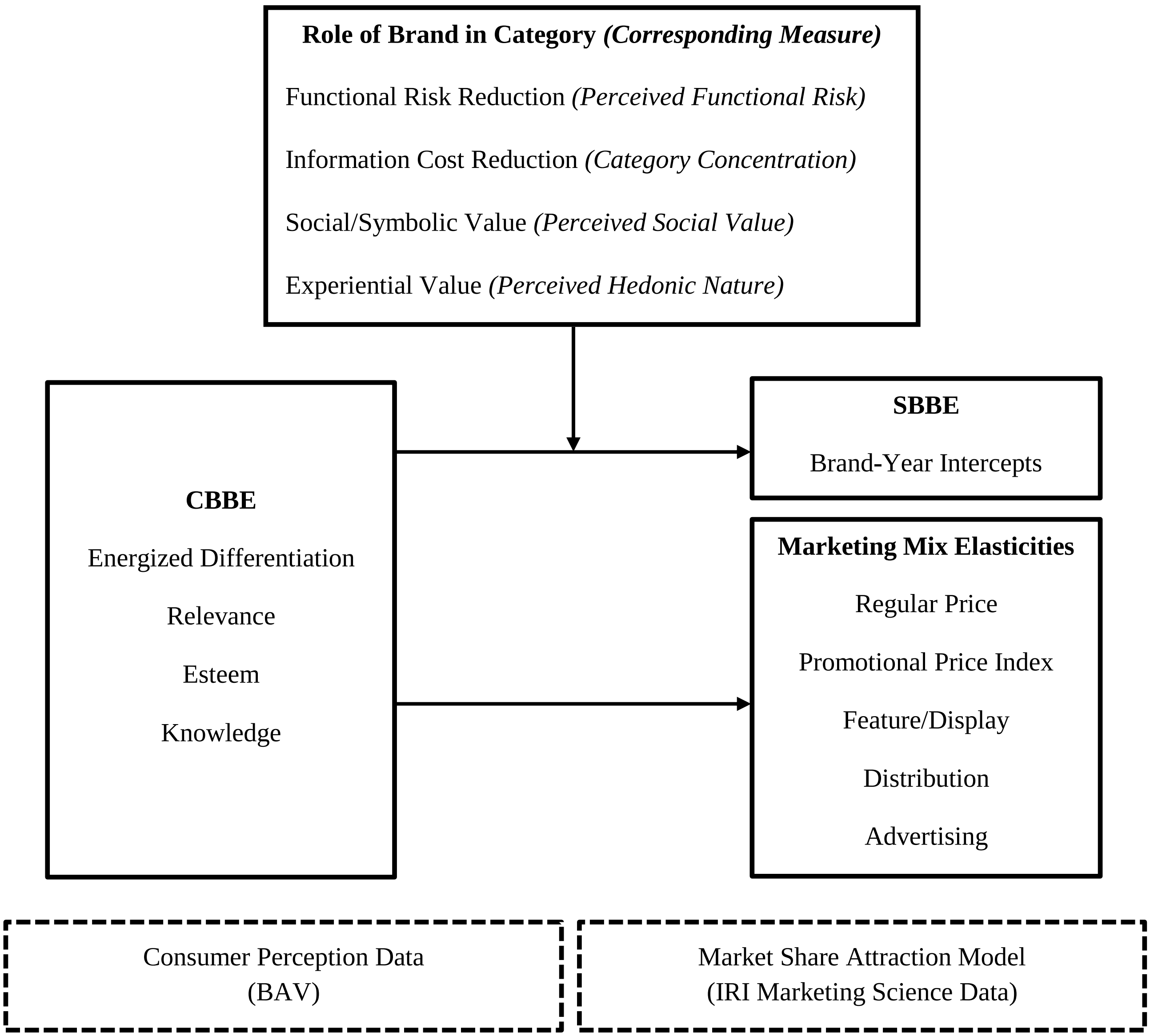
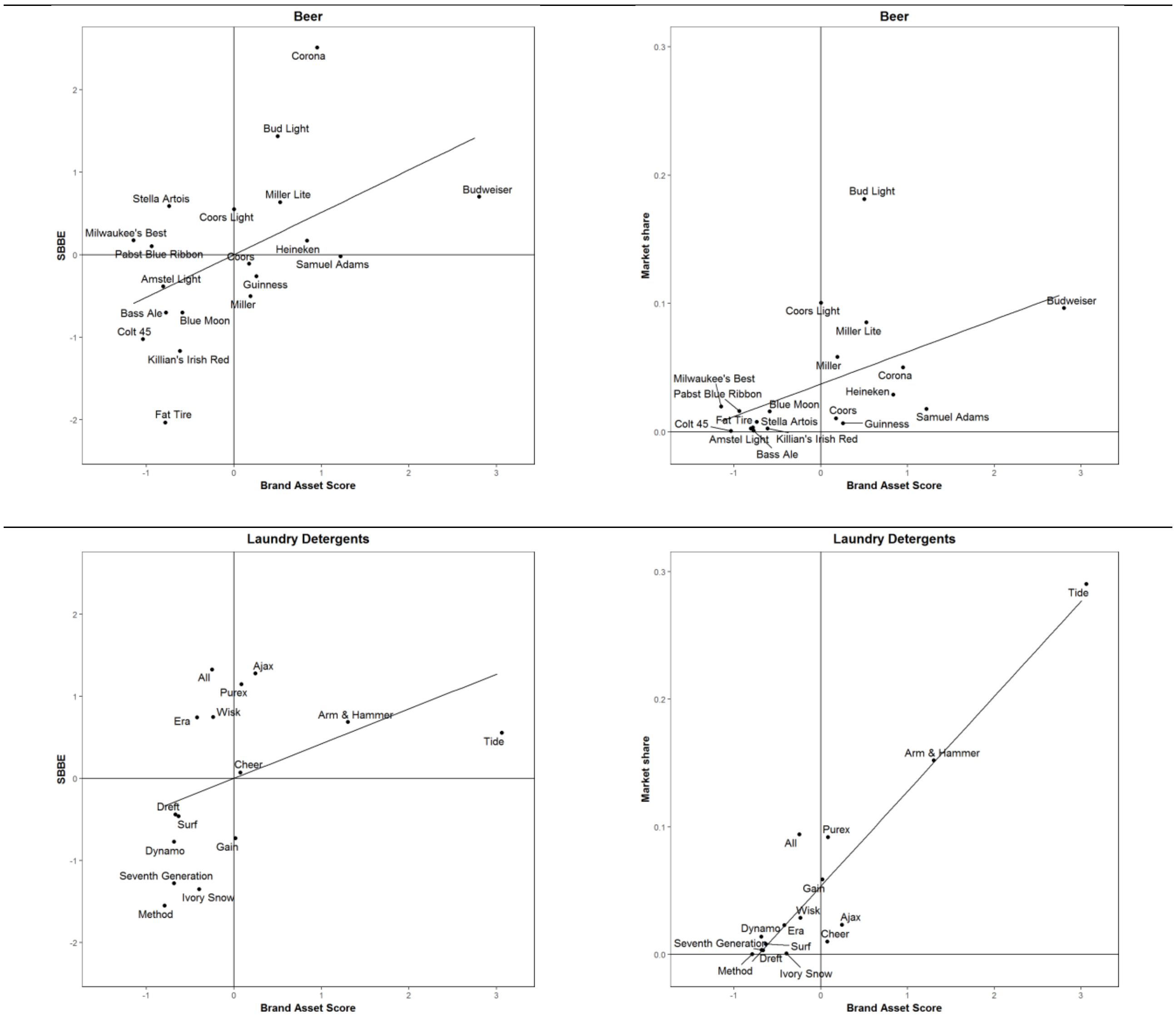


Figure 2

The Association of CBBE with SBBE and Market Share

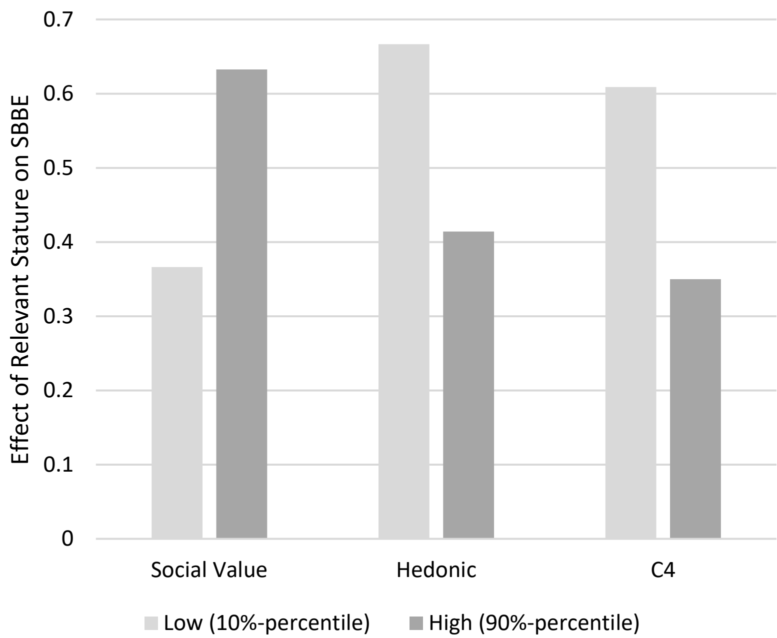


Note: Data are shown for the most recent year (2011). All measures except market share are standardized across brands to facilitate comparability. Regression lines are shown to indicate the association between the measures.

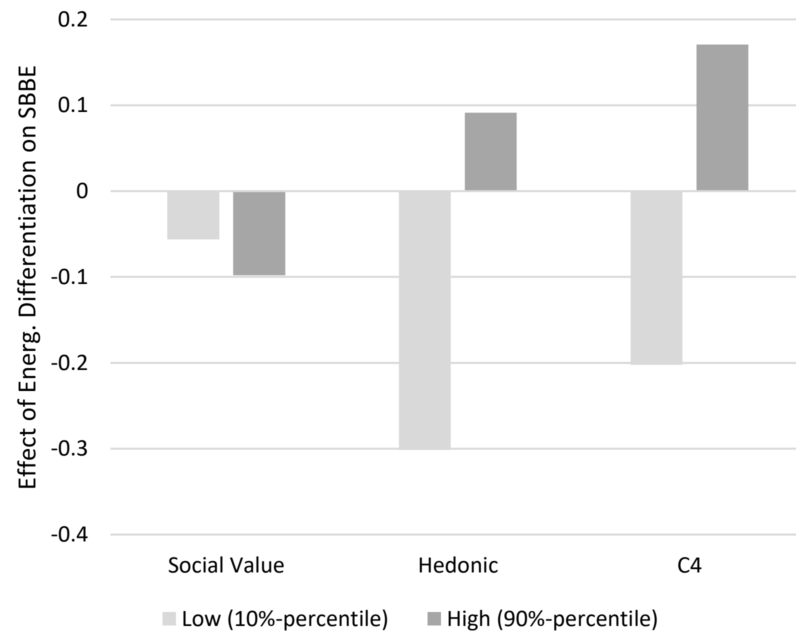
Figure 3

Effect of Relevant Stature and Energized Differentiation on SBBE for Different Levels of Moderators

A. Effect of Relevant Stature on SBBE



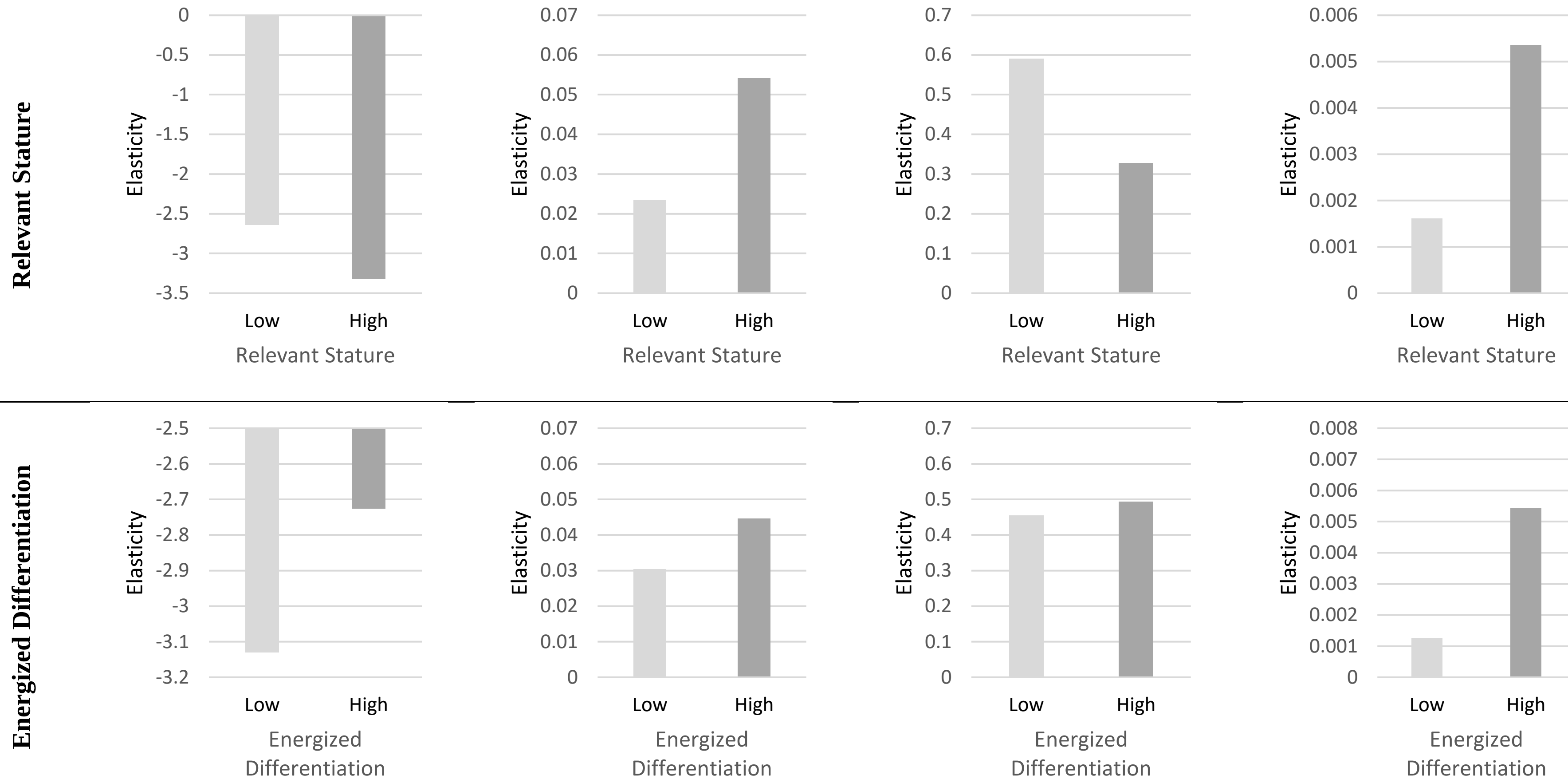
B. Effect of Energized Differentiation on SBBE



Notes: Effects are computed at the 10th and 90th percentile of the category characteristics using the regression results in Table 5.

Figure 4
Marketing Elasticities for Different Levels of CBBE

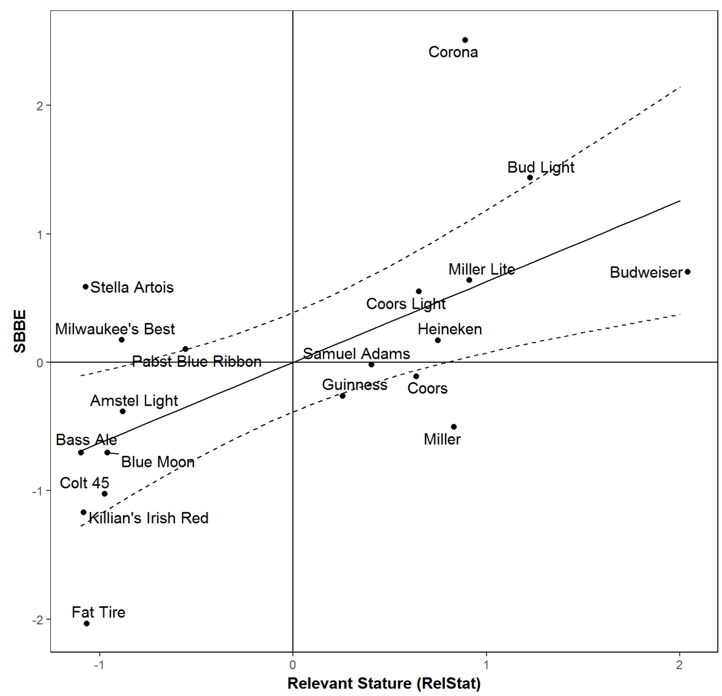
Effect of	*Effect on*			
	Promotional Price Index Elasticity	**Feature/Display Elasticity**	**Distribution Elasticity**	**Advertising Elasticity**

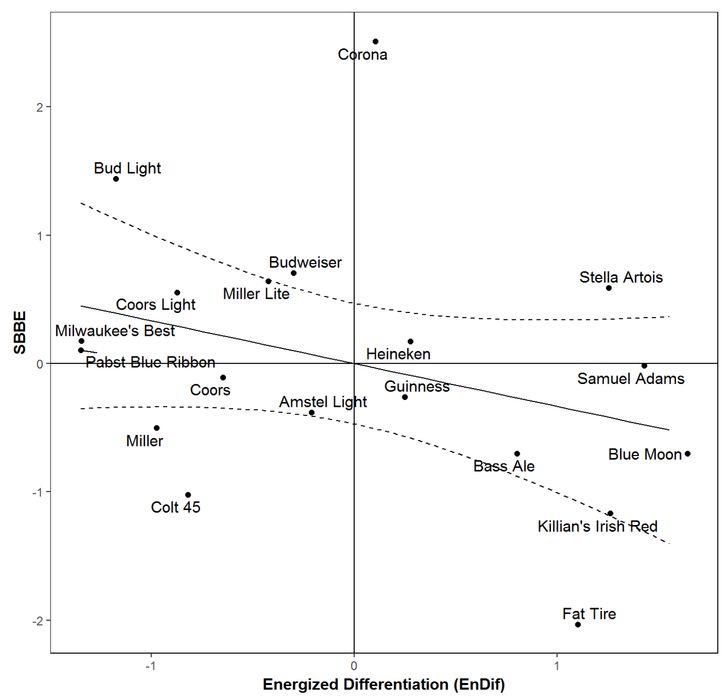


Note: Effects are computed in two steps: First, we calculate the impact of Relevant Stature and Energized Differentiation at their 10th and 90th percentiles on standardized elasticities, using the regression results in Table 6. Then, we convert the effect to raw elasticities by multiplying them with the (weighted) standard deviation of estimated elasticities, and adding their (weighted) mean.

Figure 5

Association between SBBE and CBBE: Beer Category





Note: Data are shown for the most recent year (2011), and are standardized for all measures across brands to facilitate comparability. Regression lines, with 95%-confidence bounds are shown.

Table 1

Association of CBBE with SBBE and Marketing Mix Elasticities: Propositions

CBBE dimension	**Expected Association With**					
	SBBE	**Regular Price Elasticity**	**Promotional Price Index Elasticity**	**Feature/Display Elasticity**	**Distribution Elasticity**	**Advertising Elasticity**
Relevance Esteem Knowledge (REK)	P1: REK has a **positive** association with *SBBE.* P1.1: The association between REK and SBBE is **stronger** for *higher functional risk categories*. P1.2: The association between REK and SBBE is **stronger** for *less concentrated categories*. P1.3: The association between REK and SBBE is **stronger** (more positive) for *higher social value categories*. P1.4: The association between REK and SBBE is **stronger** for *more hedonic categories*.	P3: Higher REK is associated with a **weaker** (less negative) *regular price elasticity*.	P5: Higher REK is associated with a **stronger** (more negative) *promotional price elasticity*.	P7: Higher REK is associated with a **stronger** *feature/display elasticity*.	P9: There are arguments both for a positive and a negative association of REK with *distribution elasticity*.	P11: Higher REK is associated with a **stronger** *advertising elasticity*.
Energized Differentiation (ED)	P2: ED has a **negative** association with *SBBE*. P2.1: The association between ED and SBBE is **weaker** for *higher functional risk categories*. P2.2: The association between ED and SBBE is **stronger** for *more concentrated categories*. P2.3: The association between ED and SBBE is **stronger** (more positive) for *higher social value categories*. P2.4: The association between ED and SBBE is **stronger** for *more hedonic categories*.	P4: Higher ED is associated with a **weaker** (less negative) *regular price elasticity*.	P6: Higher ED is associated with a **weaker** (less negative) *promotional price elasticity*.	P8: Higher ED is associated with a **weaker** *feature/display elasticity*.	P10: Higher ED is associated with a **weaker** *distribution elasticity*.	P12: Higher ED is associated with a **stronger** *advertising elasticity*.

Table 2

Sample Description

Category	No. of Brands	No. of BAV brands	Mean No. of Years per Brand	Mean of Social Value[a]	Mean of Hedonic Nature[a]	Mean of Functional Risk[a]	Mean of Cat. Concentration[a]
Beer	59	37	9.9	3.39	5.96	3.44	.47
Carbonated Soft Drinks	27	21	9.8	2.72	5.32	3.01	.56
Cigarettes	25	21	10.0	3.11	4.26	3.10	.65
Coffee	30	23	9.4	3.07	5.52	3.64	.74
Cold (RTE) Cereal	23	20	10.0	2.72	4.75	3.16	.48
Deodorants	19	17	9.7	2.44	2.83	3.53	.51
Disposable Diapers	6	4	9.2	2.45	2.10	3.72	.99
Household Cleaners	15	9	9.7	2.59	2.18	3.41	.59
Ketchup	5	3	10.0	2.05	3.45	2.58	1.00
Laundry Detergents	20	17	9.9	2.56	2.40	3.53	.60
Margarine & Spreads	13	6	10.0	2.17	3.09	2.72	.65
Mayonnaise	7	3	10.0	2.15	3.07	2.83	.93
Milk	19	4	9.9	2.34	3.39	2.81	.90
Mustard	12	5	10.0	2.12	3.30	2.46	.90
Peanut Butter	11	5	9.4	2.30	4.37	2.98	.92
Frozen Pizza & Dinners	26	15	9.4	2.47	3.61	3.22	.47
Razors & Blades	5	3	10.0	2.52	2.61	3.72	.99
Salty Snacks	17	7	9.6	2.56	5.16	2.97	.74
Shampoo	28	17	9.1	2.84	3.09	3.56	.57
Soup	8	6	9.0	2.16	3.40	2.94	.98
Pasta Sauce	15	14	9.6	2.30	3.89	3.05	.70
Sugar Substitutes	10	5	8.1	2.52	2.82	2.76	.89
Toilet Tissue	10	5	10.0	2.45	2.40	3.60	.70
Toothpaste	15	13	9.9	2.53	2.79	3.43	.87
Yogurt	16	10	8.9	2.43	4.03	3.01	.79

[a] Category concentration is the total market share of the top four brands in a category. Both Social Value and Functional Risk of a category are measured on two-item, 5-point Likert scales (values 1-5), with higher values representing higher scores. Hedonic Nature is measured on a two-item, 7-point sematic differential scale (values 1-7), with higher values representing more hedonic categories. Please see Web Appendix B for measurement details.

Table 3

Summary of Market Share Elasticity Estimates

Marketing Mix Variable	Elasticity estimate[a]		90%-interval of estimated elasticities
	Mean	Standard Deviation	
Regular price	-.79***	1.18	[-2.74, .53]
Promotional price index	-2.59***	1.97	[-5.64, -.45]
Feature/Display	.02***	.05	[-.04, .19]
Distribution	.40***	.47	[-.10, 1.03]
Advertising stock	.001**	.02	[-.02, .04]

[a] Weighted means and standard deviations across 441 brands in 25 categories, with weights equal to the inverse of the estimated standard errors. Significance tests based on meta-analytic Z-values.
*** $p < .01$; ** $p < .05$; * $p < .10$

Table 4

Correlations of SBBE with CBBE

	Correlation With				
CBBE Dimension	Esteem	Knowledge	Energized Diff.	SBBE	Market Share
Relevance	.85***	.64***	.02	.39***	.56***
Esteem		.70***	.04**	.35***	.55***
Knowledge			-.20***	.53***	.52***
Energized Differentiation				-.14***	-.08***

Note: Correlations computed on 2423 brand-year observations for 290 brands in 25 categories for which CBBE measures are available. Data are standardized within category before computing correlations.
*** $p < .01$; ** $p < .05$; * $p < .10$.

Table 5

Regression of SBBE on CBBE Principal Components and Category Moderators

Independent Variable	*Expectation (Proposition)*	*Estimate*	*S.E.*
Principal Component for Relevant Stature (RelStat)	+ (P1)	.52***	.04
x Category Functional Risk	+ (P1.1)	-.01	.17
x Category Concentration	− (P1.2)	-.50*	.30
x Category Social Value	+ (P1.3)	.29*	.17
x Category Hedonic Nature	+ (P1.4)	-.09**	.04
Principal Component for Energized Differentiation (EnDif)	− (P2)	-.08**	.04
x Category Functional Risk	− (P2.1)	-.08	.19
x Category Concentration	+ (P2.2)	.72***	.26
x Category Social Value	+ (P2.3)	-.05	.21
x Category Hedonic Nature	+ (P2.4)	.13***	.05
Secondary market	−	-.59***	.13
Category Social Value		-.21	.24
Category Hedonic Nature		.03	.06
Category Functional Risk		-.08	.21
Category Concentration		.26	.35
Constant		.64	.67
R^2		.47	
Number of brands		290	
Number of observations		2423	

Note: The dependent variable is a brand's SBBE, and the model is estimated using Weighted Least Squares, with weights equal to the estimated SBBE's inverse standard error. Data are standardized within category before model estimation. Robust clustered standard errors are reported.
*** $p< .01$; ** $p< .05$; * $p<.10$

Table 6

Regression of Marketing Mix Elasticities on CBBE Principal Components

CBBE Principal Component	Effect on Elasticity of: Regular Price		Promotional Price		Feature / Display		Distribution		Advertising	
	Expectation (Proposition)	Estimate (S.E.)	Expectation (Proposition)	Estimate (S.E.)	Expectation (Proposition)	Estimate (S.E.)	Expectation (Proposition)	Estimate (S.E.)	Expectation (Proposition)	Estimate (S.E.)
Relevant Stature (RelStat)	+ (P3)	-.02 (.07)	− (P5)	-.14*** (.05)	+ (P7)	.16*** (.05)	+ or − (P9)	-.19*** (.05)	+ (P11)	.07* (.04)
Energized Differentiation (EnDif)	+ (P4)	.08 (.06)	+ (P6)	.09* (.05)	− (P8)	.08 (.06)	**−** (P10)	.03 (.05)	+ (P12)	.08* (.05)
Constant		.03 (.06)		.07 (.05)		-.15** (.06)		-.05 (.05)		-.06 (.05)
R^2		.01		.06		.04		.06		.02
N		290		290		276		290		226

S.E. = standard error. *** *p*< .01; ** *p*< .05; * *p*<.10

Note: The model is estimated using Weighted Least Squares, with weights equal to the elasticities' inverse standard errors. Data are standardized within category before estimation. Hence, the variation being explained is across brands *within* a category, not across categories. N is smaller for Feature/Display and Advertising because some brands lack variation in these variables.

Table 7

Association of CBBE with SBBE and Marketing Mix Elasticities: Summary of the Findings

	Association With	
CBBE dimension	**SBBE**	**Marketing Mix Elasticities**
Relevance **Esteem** **Knowledge,** **combined in Relevant Stature**	• Positive and significant correlation between SBBE and Relevance (.39), Esteem (.35) and Knowledge (.53). • The effect of Relevant Stature on SBBE is significantly positive (P1 supported). • The effect of Relevant Stature on SBBE is stronger for ○ less concentrated categories (P1.2 supported). ○ high social value categories (P1.3 supported). ○ less hedonic categories (P1.4 not supported). but it is not significantly moderated by ○ functional risk (P1.1 not supported)	Higher Relevant Stature is associated with • no significant difference in regular price elasticity (P3 not supported) • a stronger (more negative) promotional price elasticity (P5 supported). • a stronger feature/display elasticity (P7 supported). • a weaker distribution elasticity (P9 no prediction). • a stronger advertising elasticity (P11 supported).
Energized Differentiation	• Negative and significant correlation between SBBE and Energized Differentiation (-.14). • The effect of its principal component on SBBE is significantly negative (P2 supported). • The effect of Energized Differentiation on SBBE is stronger for ○ more concentrated categories (P2.2 supported). ○ more hedonic categories (P2.4 supported). but it is not significantly moderated by ○ functional risk (P2.1 not supported). ○ social value (P2.3 not supported).	Higher Energized Differentiation is associated with • no significant difference in regular price elasticity (P4 not supported). • a weaker (less negative) promotional price elasticity (P6 supported). • no significant difference in feature/display elasticity (P8 not supported). • no significant difference in distribution elasticity (P10 not supported). • a stronger advertising elasticity (P12 supported).

Web Appendix A

Consumer-Based Brand Equity Measures from Brand Asset Valuator (BAV)[a]

CBBE Dimension	Items	Survey Statements	Item Scales
Energized Differentiation	Dynamic Innovative Distinctive Unique Different	We would like to know whether or not you associate each characteristic with each brand. Please place an "X" in the box for each characteristic which applies to the brand.	Yes or No
Relevance	Relevance	By "relevance" we mean how appropriate the brand is for you personally. Please put an "X" in the box that best describes how relevant you think it is for you.	7-point scale: Not at all (1) – Extremely Relevant (7)
Esteem	Regard	By "personal regard" we mean how highly you think and feel about the brand. Please put an "X" in the box that best describes how highly you think and feel about the brand.	7-point scale: Extremely Low (1) – Extremely High Regard (7)
	Leader Reliable High Quality	Please place an "X" in the box for each characteristic which applies to the brand.	Yes or No
Knowledge	Familiarity	By "familiarity" we mean your overall awareness of the brand as well as your understanding of what kind of product or service the brand represents. Please put an "X" in the box that best describes how familiar you are with it.	7-point scale: Never Heard of (1) – Extremely Familiar (7)
Brand Asset Score			Product of rescaled values of the four dimensions

[a] Documentation from Young & Rubicam. More information about BAV can be found at bavconsulting.com.

Web Appendix B

Operationalization of Category Characteristics

Construct	Symbol	Measures	Scale	Adapted from
Hedonic nature of category (Cronbach α = .81)	Hed_c	Please rate category X on how Not Fun / Fun it is. Please rate category X on how Unenjoyable / Enjoyable it is.	7-point semantic differential scale: Not Fun = 1; Fun = 7 Unenjoyable = 1; Enjoyable = 7	Voss, Spangenberg, and Grohmann, (2003)
Functional risk (Cronbach α = .60)	$PerfRisk_c$	There is much to lose if you make the wrong choice in category X. In category X, there are large differences in quality between the various products.	5-point Likert scale: 1= strongly disagree; 2 = somewhat disagree; 3 = neither agree nor disagree; 4 = somewhat agree; 5 = strongly agree.	Steenkamp and Geyskens (2014) Own development
Social value (Cronbach α = .85)	$Social_c$	You can tell a lot about a person from the brand of category X he or she buys. The brand of category X a person buys says something about who they are.	5-point Likert scale: 1= strongly disagree; 2 = somewhat disagree; 3 = neither agree nor disagree; 4 = somewhat agree; 5 = strongly agree.	Steenkamp and Geyskens (2014)
Concentration	$C4_c$	C4: market share of the four largest brands in the category		Tirole (1988)

Web Appendix C

Operationalization of Variables in Market Share Attraction Model

Variable	Symbol	Operationalization
Market share	MS_{bt}	Number of units (in volume equivalents) of all SKUs of brand b sold in week t, divided by total units of category sold in week t.
Regular price	$RegPrice_{bt}$	SKU- and store-weighted[a] regular price of brand b in week t, defined for each available SKU as the highest actual price (dollar revenue divided by units sold) per equivalent volume of the SKU in the most recent four weeks (t, t-1, t-2, t-3), and deflated by the consumer price index of the product category[b].
Price index	$PriceIndex_{bt}$	SKU- and store-weighted[a] ratio of actual price to regular price (RegPrice) for brand b in week t. Suppose an SKU's regular price is $2.00 and its actual price is $1.50, then the price index is $1.50/$2.00 = .75, reflecting a 25% promotional price discount.
Feature/Display	FD_{bt}	SKU- and store-weighted[a] indicator variable for whether or not each available SKU of brand b has a feature and/or display in week t.
Total distribution	$Distr_{bt}$	Store-weighted[c] total distribution of brand b in week t, defined as a brand's share of total SKUs available in store in week t.[d] Suppose there are 100 (same-size) stores and each carries a total of 50 SKUs in the category. The focal brand is sold in 80 stores, and has 10 SKUs in each of them. The total distribution is (80*10)/(100*50) = .16 or 16%. Total distribution is the same as the product of distribution breadth (80/100 in the example) and distribution depth (10/50 in the example): (80*10)/(100*50) = (80/100)*(10/50) = .16.
Advertising	$Advertising_{bt}$	Total monthly advertising spending of brand b in week t[e].

[a] To aggregate SKU-level metrics to brand-level metrics, we first compute weighted averages of the focal variables across a brand's SKUs within each store stocking the brand, using as weights the SKU's share of brand sales in the store in a rolling window of the previous quarter (13 weeks). Then, we aggregate across all stocking stores, with weights equal to each store's share of total category sales in the same rolling window.
[b] Data taken from the Bureau of Labor Statistics (http://www.bls.gov/cpi).
[c] Weights are equal to each store's share of total category sales in a rolling window of the previous quarter.
[d] An SKU is assumed to be available in a store in week t if it has non-zero sales at least once in the most recent four weeks (t, t-1, t-2, t-3).
[e] To compute weekly advertising spending, we first divide by the number of days in a month, and then sum up the spending in 7-day periods that correspond to IRI's definition of a week.

Web Appendix D

Product Attributes Included in Market Share Model

Category	Attribute	Levels[a]
~~Beer~~	Type of Beer Ale	Ale, Malt, Stout, Lager, Other
Beer	Package	Bottle, Can, Other
Carbonated Soft Drinks	Package	Bottle, Can, Glass, Other
Carbonated Soft Drinks	Flavor Scent	Cola, Ginger, Root, Other
Carbonated Soft Drinks	Calorie Level	Reg, Lowcal
Carbonated Soft Drinks	Product Type	Soda, Water
Cigarettes	Type of Cigarette	Filter, Other
Cigarettes	Size	King85, Long100, Other
Cigarettes	Menthol Info	Nonmenth, Other
Coffee	Caffeine Info	Decaf, Lowcaf
Cold (RTE) Cereal	Package	Box, Other
Cold (RTE) Cereal	Type of Grain	Corn, Oat, Wheat, Bran, Whole, Granola, Other
Cold (RTE) Cereal	Flavor Scent	Regular, Honey, Cocoa, Cinnamon, Other
Deodorants	Product Type	Antiper, Deo
Deodorants	Package	Container, Other
Deodorants	Form	Solid, Stick, Gel, Spray, Other
Disposable Diapers	User Info	Boy, Girl, Baby, Other
Disposable Diapers	Product Type	Diaper, Tpant
Disposable Diapers	Weight of Baby	Lt20, Up40, Gt40, Other
Disposable Diapers	Stage Phase	Stg1, Stg2, Stg3, Stg4, Stg5, Stg6, Infant, Other
Household Cleaners	Product Type	Cleaner, Toilet, Other
Household Cleaners	Form	Liquid, Spray, Solid, Gel, Foam, Other
Ketchup	Package	Jar, Other
Laundry Detergents	Package	Bottle, Box, Bag, Other
Laundry Detergents	Concentration Level	Ultra, Double, Triple, Gt3, Classic, Other
Laundry Detergents	Form	Liquid, Powder, Sheet, Pod, Other
Margarine & Spreads	Package	Tub, Bottle, Box, Other
Margarine & Spreads	Product Type	Marg, Btr_blend, Vegoil_sprd
Margarine & Spreads	Flavor Scent	Regflv, Swtcrm, Butter, Btrmlk, Other
Margarine & Spreads	Type of Margarine	Vegoil, Cornoil, Oliveoil, Soyoil, Canolaoil, Flaxoil, Other
Margarine & Spreads	Calorie Level	Regcal, Other
Margarine & Spreads	Form	Spread, Stick, Spray, Other
Mayonnaise	Flavor Scent	Regflv, Garlicflv, Mustflv, Tomflv, Lime, Hradflv, Other
Mayonnaise	Package	Gjar, Pjar, Squeeze, Other
Mayonnaise	Sugar Content	Regsug, Lowsug, Other
Milk	Package	Bottle, Carton, Other
Milk	Flavor Scent	Regflv, Strawberry, Chocolate, Vanilla, Other
Milk	Type of Milk	Regular, Reduced_fat, Low_fat, Other

Category	Attribute	Levels[a]
Mustard	Package	Jar, Other
Peanut Butter	Texture	Smooth, Crunchy, Chunky, Other
Peanut Butter	Flavor Scent	Regular, Other
Frozen Pizza & Dinners	Product Type	Entr_din, Burito/Tamale, Sandwich/panini, Pizza, Other
Razors & Blades	Package	Box, Bag, Card, Other
Razors & Blades	Form	Single, Twin, Triple, Multiple, Other
Salty Snacks	Package	Bag, Tin, Other
Salty Snacks	Flavor Scent	Regular, Cheese, Barbecue, Sourcream, Salt_vin, Other
Salty Snacks	Product Type	Potato, Tortilla
Shampoo	Type of Shampoo	Regular, Moistur, Volum, Dandruff, Color, Cleansing, Other
Shampoo	Product Type	Shampoo, Combo
Shampoo	Flavor Scent	Regular, Herbal, Other
Shampoo	Form	Liquid, Other
Soup	Product Type	Soup, Broth
Pasta Sauce	Type of Italian Sce	Pasta, Bruschetta, Other
Pasta Sauce	Flavor Scent	Regular, Mushroom, Meat, Garlic, Cheese, Marinara, Other
Pasta Sauce	Product Type	Pastasc, Italian, Spagsc
Sugar Substitutes	Type of Sugar	Aspartame, Sucralose, Agave, Saccharin, Other
Sugar Substitutes	Form	Packet, Liquid, Granul, Other
Toilet Tissue	Package	Plastic, Paper, Box, Other
Toilet Tissue	Color	White, Other
Toilet Tissue	Number of Ply	Ply2, Other
Toothpaste	Type of Formula	Whitening, Cavity, Sensitive, Other
Toothpaste	Additives	Fluoride, Peroxide, Other
Toothpaste	Form	Paste, Gel, Strips, Other
Toothpaste	Flavor Scent	Regular, Mint, Other
Toothpaste	Package	Tube, Other
Toothpaste	Product Type	Toothpaste, Whitener
Yogurt	Flavor Scent	Berry, Plain, Peach, Vanilla, Other
Yogurt	Package	Bottle, Cup, Container, Other
Yogurt	Product Type	Yogurt, Smoothie, Drink
Yogurt	Fat Content	Lowfat, Nonfat, Other

[a] The last level of each attribute represents the base case level which is excluded for identification.

Web Appendix E

Elasticities by Category

	Regular price						Price index						Feature/Display						Distribution						Advertising						
Category	B	Mean[a]	Med.	SD	Sig.>0	Sig.<0	B	Mean[a]	Med.	SD	Sig.>0	Sig.<0	B	Mean[a]	Med.	SD	Sig.>0	Sig.<0	B	Mean[a]	Med.	SD	Sig.>0	Sig.<0	B	Mean[a]	Med.	SD	Sig.>0	Sig.<0	λ
Beer	59	-1.96	-2.04	1.54	2%	81%	59	-4.38	-4.37	2.12	0%	90%	58	.04	.03	.07	41%	7%	59	.55	.48	.46	78%	0%	46	-.001	-.001	.012	7%	13%	.10
Carbonated Soft Drinks	27	-.87	-1.00	1.39	4%	74%	27	-3.09	-3.19	1.05	0%	89%	27	.16	.16	.28	48%	4%	27	.37	.33	.45	78%	7%	21	-.004	-.005	.020	14%	29%	.90
Cigarettes	25	-.74	-.75	1.07	4%	72%	25	-.46	-.64	1.33	16%	44%	16	.00	.00	.00	13%	6%	25	.30	.29	.24	84%	0%	14	-.001	-.001	.014	14%	21%	.90
Coffee	30	-.60	-.69	1.29	7%	40%	30	-3.12	-3.42	3.30	0%	80%	30	.02	.01	.12	33%	17%	30	.48	.44	.94	60%	0%	20	-.002	.001	.038	15%	10%	.90
Cold (RTE) Cereal	23	-1.18	-1.37	1.09	9%	57%	23	-2.95	-3.10	1.38	0%	87%	23	.04	.03	.06	26%	0%	23	.22	.25	.33	52%	4%	22	.011	.015	.034	32%	0%	.60
Deodorants	19	.07	-.05	1.33	16%	21%	19	-3.88	-3.68	1.46	0%	100%	19	.06	.06	.06	79%	5%	19	.60	.46	.49	58%	0%	16	.010	.007	.053	19%	13%	.90
Disposable Diapers	6	-.33	-.46	.67	17%	50%	6	-1.61	-2.43	1.31	0%	67%	6	.02	.03	.04	33%	0%	6	.05	.05	.35	17%	17%	4	-.003	-.004	.005	0%	0%	.90
Household Cleaners	15	-.75	-.98	2.69	7%	60%	15	-3.65	-3.81	1.19	0%	93%	15	.03	.02	.05	67%	7%	15	.34	.37	.23	93%	0%	11	.022	.017	.083	27%	0%	.90
Ketchup	5	-1.58	-1.89	.90	0%	60%	5	-2.22	-2.41	.75	0%	60%	5	.13	.17	.09	80%	0%	5	.03	-.01	.16	0%	0%	1	.005	.005	NA	0%	0%	.70
Laundry Detergents	20	-.85	-.93	.49	0%	80%	20	-3.25	-3.53	2.39	0%	80%	20	.02	.05	.13	45%	5%	20	.45	.31	.36	60%	0%	11	-.007	.004	.044	0%	18%	.90
Margarine & Spreads	13	-.72	-.89	.45	0%	69%	13	-2.26	-2.38	.68	0%	100%	13	.05	.05	.05	85%	0%	13	-.01	-.04	.23	15%	15%	7	.005	.006	.011	14%	0%	.60
Mayonnaise	7	-1.24	-1.09	.75	0%	86%	7	-3.10	-3.17	.51	0%	100%	7	.11	.10	.05	71%	0%	7	-.05	-.20	.31	0%	14%	3	-.012	-.005	.015	0%	33%	.90
Milk	19	-.20	-.12	.59	5%	26%	19	-.62	-.47	1.24	0%	68%	19	.00	.00	.02	21%	26%	19	.20	.24	.34	47%	11%	17	.000	-.001	.022	12%	0%	.90
Mustard	12	-.81	-.72	1.11	8%	75%	12	-2.49	-2.64	1.18	0%	92%	12	.04	.03	.04	75%	0%	12	.48	.64	.51	67%	0%	3	.001	.002	.002	33%	0%	.10
Peanut Butter	11	-.35	-.60	5.82	27%	27%	11	-3.06	-4.03	1.30	0%	100%	11	.01	.00	.07	36%	9%	11	.18	.18	.37	45%	0%	5	.000	.001	.019	0%	0%	.90
Frozen Pizza & Dinners	26	-1.37	-1.48	1.54	4%	73%	26	-4.15	-4.29	1.11	0%	100%	25	.03	.04	.12	32%	4%	26	.46	.41	.35	58%	4%	19	.002	.003	.035	16%	16%	.80
Razors & Blades	5	-.18	-.22	.34	0%	20%	5	-3.04	-2.98	1.43	0%	100%	5	.05	.03	.07	60%	0%	5	.28	.36	.79	20%	0%	2	.005	.019	.025	0%	0%	.60
Salty Snacks	17	-.85	-.83	1.10	0%	65%	17	-2.36	-2.41	1.24	0%	94%	17	.14	.16	.21	47%	0%	17	.26	.08	.48	41%	6%	13	.002	.000	.034	23%	23%	.70
Shampoo	28	-.54	-.19	1.31	11%	32%	28	-1.59	-1.29	2.84	11%	54%	27	.07	.07	.10	74%	0%	28	.70	.78	.53	86%	0%	18	.002	.007	.048	22%	17%	.90
Soup	8	-.10	-.91	2.12	13%	63%	8	-3.04	-3.65	1.70	0%	100%	7	.05	.06	.06	100%	0%	8	.27	.47	.37	63%	0%	4	.007	.006	.010	25%	0%	.40
Pasta Sauce	15	-1.40	-1.31	1.78	20%	67%	15	-3.37	-3.78	2.43	7%	93%	15	.02	.02	.06	40%	7%	15	1.04	.74	1.17	73%	0%	8	.008	.016	.040	13%	13%	.90
Sugar Substitutes	10	-.72	-.57	3.17	0%	60%	10	-1.25	-1.50	4.67	10%	60%	8	.00	.00	.02	38%	0%	10	.57	.63	.71	80%	0%	6	-.001	.000	.033	0%	0%	.80
Toilet Tissue	10	-1.13	-.75	1.94	20%	40%	10	-3.74	-3.88	2.29	0%	90%	10	.08	.09	.17	60%	10%	10	.20	.02	.34	30%	0%	5	-.003	-.001	.039	0%	0%	.80
Toothpaste	15	-.33	-.56	1.04	7%	33%	15	-3.64	-3.97	1.40	0%	93%	15	.04	.04	.09	73%	0%	15	.45	.44	.46	60%	0%	11	-.002	-.003	.022	9%	9%	.90
Yogurt	16	-.58	-.69	2.17	19%	56%	16	-3.15	-3.31	1.41	0%	94%	16	.01	.00	.09	38%	13%	16	.63	.46	.88	75%	6%	10	.020	.015	.022	30%	0%	.90

[a] Weighted mean, with weights equal to the estimated elasticity's inverse standard error.
Note: B = Number of brands. λ = Advertising smoothing constant.

Web Appendix F

Table F1

Regression of SBBE on CBBE Principal Components and Category Moderators (Effects Reported by CBBE Dimensions Underlying Principal Components)

Independent Variable	Estimate	SE	t	p
Relevance	.16***	.01	12.24	<.01
x Category Social Value	.09	.06	1.51	.13
x Category Hedonic Nature	-.02	.01	-1.22	.22
x Category Functional Risk	-.01	.06	-.17	.87
x Category Concentration	-.11	.10	-1.09	.28
Esteem	.19***	.01	13.06	<.01
x Category Social Value	.10*	.06	1.65	.10
x Category Hedonic Nature	-.03*	.02	-1.77	.08
x Category Functional Risk	-.01	.06	-.11	.91
x Category Concentration	-.17	.11	-1.51	.13
Knowledge	.25***	.02	13.98	<.01
x Category Social Value	.14*	.08	1.79	.07
x Category Hedonic Nature	-.06***	.02	-3.09	<.01
x Category Functional Risk	.00	.08	.05	.96
x Category Concentration	-.34***	.13	-2.54	.01
Energized Differentiation	-.10***	.04	-2.80	.01
x Category Social Value	-.05	.20	-.25	.81
x Category Hedonic Nature	.13***	.05	2.79	.01
x Category Functional Risk	-.07	.18	-.39	.69
x Category Concentration	.73***	.25	2.86	<.01
Secondary market	-.59***	.13	-4.54	<.01
Category Social Value	-.21	.24	-.88	.38
Category Hedonic Nature	.03	.06	.50	.62
Category Functional Risk	-.08	.21	-.38	.70
Category Concentration	.26	.35	.74	.46
Constant	.64	.67	.96	.34
R-squared	.47			
Number of brands	290			
Number of observations	2423			

Note: The model is estimated using Weighted Least Squares, with weights equal to the estimated SBBE's inverse standard error. Data are standardized within category before model estimation. Robust Clustered Standard Errors are reported. The original model regresses SBBE on the independent variables that include the interactions between the principal components for RelStat and EnDiff and category-level moderators. To calculate the impact of the four CBBE dimensions underlying the principal components, we use 1 category-level SD shifts in each respective CBBE dimension (for computational details, see below).

*** $p < .01$; ** $p < .05$; * $p < .10$

Table F2

Regression of Marketing Mix Elasticities on CBBE Principal Components (Effects Reported by CBBE Dimensions Underlying Principal Components)

	Estimated Effect on Elasticity of				
CBBE Dimension	Regular Price	Promotional Price	Feature / Display	Distribution	Advertising
Relevance	.00	-.03***	.05***	-.05***	.03***
	(.02)	(.01)	(.02)	(.01)	(.01)
Esteem	.00	-.05***	.06***	-.07***	.03***
	(.02)	(.01)	(.02)	(.01)	(.01)
Knowledge	-.02	-.08***	.06***	-.09***	.02***
	(.03)	(.02)	(.01)	(.02)	(.00)
Energized Differentiation	.08	.09*	.07	.03	.07*
	(.05)	(.05)	(.05)	(.05)	(.04)
Constant	0.03	0.07	-.15**	-0.05	-0.06
	-0.06	-0.05	-0.06	-0.05	-0.05
R-squared	0.01	0.06	0.04	0.06	0.02
N	290	290	276	290	226

Standard errors in parentheses. *** $p< .01$; ** $p< .05$; * $p<.10$

Note: The model is estimated using Weighted Least Squares, with weights equal to the elasticities' inverse standard errors. Data are standardized within category before model estimation. Hence, the variation being explained is across brands *within* a category, not across categories. N is smaller for Feature/Display and Advertising because some brands do not engage into advertising or feature/display promotions, or because these variables lack sufficient variation and are hence excluded from the models for some brands. The original model regresses elasticities on the principal components for RelStat and EnDiff. To calculate the impact of the four CBBE dimensions underlying the principal components, we use 1 category-level SD shifts in each respective CBBE dimension (for computational details, see below).

Computational details to derive the impact of the CBBE dimensions from the estimated coefficients of the principal component scores

The analyses reported in Tables 5 and 6 in the paper assess the impact of the principal components RelStat and EnDiff on SBBE and marketing mix elasticities. These components have been derived from the original CBBE dimensions Relevance, Esteem, Knowledge, and Energized Differentiation. The principal components (PC) can be computed as:

$$\mathrm{PC_{by}} = \mathrm{CBBE_{by}} \cdot \mathrm{E} \qquad \text{(F1)}$$

where

PC_{by}	denotes the rotated components for brand b in year y (dimension: N x 2),[1] consisting of the column vectors $RelStat_{by}$ and $EnDiff_{by}$; N = Number of observations;
$CBBE_{by}$	are the standardized CBBE dimensions (dimension: N x 4); and
E	is the eigenvector matrix obtained from PCA, where the eigenvectors of the smallest principal components (Eigenvalues < 1) have been dropped (dimension: 4 x 2).

Because of this linear relationship between the component scores PC_{by} and the CBBE dimensions $CBBE_{by}$, we can trace back the impact of the original CBBE dimensions on SBBE and marketing mix elasticities as described next.

In a standard principal component regression, we could pre-multiply the parameter estimates of the two component scores on the dependent variable [2 x 1] by the [4 x 2] eigenvector matrix E

[1] Our formalization applies to estimating $SBBE_{by}$; note that we drop subscript y for the elasticity regressions, as elasticities do not vary over time. For the elasticity regressions, we use brand-level means for $CBBE_b$.

to obtain a [4 x 1] vector of estimates of the four CBBE dimension on the dependent variable and derive standard errors using the delta method (Rust, Lemon, and Zeithaml 2004).

However, in our model, we have standardized the component scores PC_{by} by category before estimation. Therefore, a stylized regression with only main effects would read as:

$$SBBE_{by} = \alpha + \beta \cdot Z(PC_{by}) \tag{F2}$$

where

$SBBE_{by}$	is the dependent variable (here: brand equity) for brand by in year y, standardized by category;
α	is the intercept;
β	are the estimated response parameters for the principal components; and
$Z(\cdot)$	is a function which standardizes its argument by category, using observed means and standard deviations from PC_{by}.

We want to calculate the change in SBBE due to a 1-standard deviation change in one dimension of CBBE. In a first step, we have to calculate of the change in CBBE on the principal component, leading to a new value PC'_{by}. Recalling eq. (F1), we can compute PC'_{byk} for a shock in the k^{th} CBBE dimension as:

$$PC'_{byk} = (CBBE_{by} + STD_{by} \cdot S_k) \cdot E \tag{F3}$$

where

PC'_{byk}	are the new component scores [N x 2] when CBBE dimension k is shifted by one category-level standard deviation;

STD_{by} are category-level standard deviations of $CBBE_{by}$ [N x 4];

S_k is a 4 x 4 matrix with zeros, except for the k^{th} diagonal element that is 1 (if the k the dimension is shocked).

Hence equation (F3) expresses the impact of a shock of an individual CBBE dimension k on the component scores PC_{by}. The next equation (F4) calculates the impact of this change on the dependent variable, which is B_k, the quantity of interest:

$$B_k = \left(Z\left(PC'_{byk}\right) - Z\left(PC_{byk}\right)\right) \cdot \beta \tag{F4}$$

To account for uncertainty in the parameter estimate β , we draw D = 1,000 draws from the variance-covariance matrix of the model in equation (F2) at the mean of the estimated parameter vector, and save the draws for β, denoted as β^d. We then extend equation (F4) by superscript d:

$$B_k^d = \left(Z\left(PC'_{byk}\right) - Z\left(PC_{byk}\right)\right) \cdot \beta^d \tag{F5}$$

where

B_k^d is a [N x 1] vector with the impact of CBBE dimension k on the dependent variable for each of the N observations for draw β^d.

Last, to summarize the impact of a change in CBBE dimension k on the dependent variable, we first average over the N observations for each draw, $\overline{B}_k^d = \sum_{n=1}^{N} \frac{1}{N} B_{kn}^d$, and then compute means and standard deviations (i.e., standard error) of $\overline{B}_k^d$.

Web Appendix G

Regression of Marketing Mix Elasticities on CBBE Principal Components and Category Moderators

CBBE Principal Component	(1) Regular Price	(2) Promotional Price	(3) Feature / Display	(4) Distribution	(5) Advertising
Relevant Stature (RelStat)	-.01	-.15***	.13**	-.19***	.08
	(.05)	(.05)	(.05)	(.05)	(.05)
x Category Social Value	.04	.11	.26	-.13	-.02
	(.21)	(.19)	(.32)	(.23)	(.16)
x Category Hedonic Nature	.03	.02	-.10	.07	.02
	(.06)	(.05)	(.06)	(.06)	(.05)
x Category Functional Risk	.06	.19	.13	.06	.19
	(.21)	(.15)	(.26)	(.19)	(.18)
x Category Concentration	-.10	.04	-.30	.39	1.27***
	(.36)	(.37)	(.32)	(.32)	(.41)
Energized Differentiation (EnDif)	.12*	.11**	.06	.03	.09**
	(.06)	(.05)	(.06)	(.05)	(.04)
x Category Social Value	-.42	.30	-.32	-.01	-.62***
	(.26)	(.27)	(.38)	(.22)	(.24)
x Category Hedonic Nature	-.06	-.17**	.05	-.10*	.14***
	(.06)	(.07)	(.07)	(.06)	(.05)
x Category Functional Risk	.23	-.07	.26	.15	.96***
	(.20)	(.24)	(.31)	(.19)	(.19)
x Category Concentration	-.60	-.44	-.73**	-1.16***	.15
	(.39)	(.38)	(.30)	(.34)	(.34)
Secondary market	-.11	.19	-.04	.19	-.13
	(.14)	(.12)	(.11)	(.14)	(.17)
Category Social Value	.41	-.12	-.50*	-.22	-.04
	(.25)	(.30)	(.28)	(.26)	(.26)
Category Hedonic Nature	-.12*	.04	.24***	.04	.02
	(.06)	(.07)	(.06)	(.06)	(.07)
Category Functional Risk	-.21	.21	.28	.14	.03
	(.23)	(.25)	(.23)	(.24)	(.25)
Category Concentration	.37	.55	.01	-.67*	.74*
	(.36)	(.40)	(.31)	(.38)	(.38)
Constant	-.16	-.86	-.62	.35	-.61
	(.82)	(.75)	(.66)	(.79)	(.83)
R-squared	.09	.13	.18	.15	.13
N	290	290	276	290	226

Standard errors in parentheses. *** $p < .01$; ** $p < .05$; * $p < .10$

Note: Data are standardized within category. Hence, the variation being explained is across brands *within* a category, not across categories. N is smaller for Feature/Display and Advertising because these variables are not in the models for some brands due to lack of variation.